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DESIGN MIX OPTIMIZATION OF HEAVY WEIGHT CONCRETE COATING PROCESS AT PT XYZ BY BOX-BEHNKEN DESIGN EXPERIMENT

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DESIGN MIX OPTIMIZATION OF HEAVY WEIGHT CONCRETE COATING PROCESS AT PT XYZ BY BOX-BEHNKEN DESIGN EXPERIMENT

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ABSTRACT

The annual production of heavy concrete in PT XYZ is about 75,000 upto 100,000 metric tons which consist of approximately 83% heavy aggregate (i.e. iron ore), 12% portland cement, and 5% water. To improve the competitive advantage of the company, PT XYZ intends to modify the existing design mix by adding certain amount of medium density material (e.g. crushed stone) in to the mixture while reducing the amount of the heavy aggregates and maintaining its CTQ characteristics. The CTQ characteristics of the product are compressive strength and density. The density of the product depends on the individual density and the proportion of the aggregates in the mixture, while the compressive strength depends mostly on the water to cement ratio.

Based on the results obtained from this research it is concluded that the optimum proportion (by volume) of the new design mix are 0,071 (water), 0,097 (cement), 0,357 crushed stone, and 0,475 (coarse iron ore) for density minimum of 3040 kgs/m3 and minimum compressive strength 40 MPa. The new design mix will potentially save 19% of the material cost compared to the old design mix.

Key words: Concrete Weight Coating, Heavy Concrete, CWC, heavy aggregate, Box-behnken

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PREFACE

Bismillahirrahmanir rahim.

This thesis was written for my Master degree in Management of Technology at Institut Teknologi Sepuluh Nopember, Surabaya. The project focused on finding the optimum design mix of heavy concrete which will reduced the cost of material. The background of this subject is my interest to improve the performace and quality of the concrete coating process in the company where I work for. The idea to improve CWC process was supported by the management. Without their support this project would not have been done, and for that I would like to thank to them all.

I would like to thank also to the following people, without whose help and support this thesis would not have been possible. First I like to show my gratitude and honnor to my supervisor Prof. Moses L Singgih for his suggestions, encouragements and guidance in writing the thesis and approaching the different challenges during the thesis. Also to Prof. Budi Santosa and Dr. Bambang Syairuddin for all the input and thoughts about the subject during the proposal stage. I want to thank MMT-ITS staff for their helpfull support. And finally I would like to thank to my wife, my children, and numerous friends who endured this long process with me, always offering support, help and love.

Alhamdulillahi rabbil ‘alamiin.

Surabaya, June 2017

Siens Harianto

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CHAPTER 1
INTRODUCTION

1.1 Background

PT XYZ is a manufacturer of line pipe for oil and gas transportation pipeline, and applicator of anticorrosion coating, insulation, and heavy weight concrete (HWC) coating products. HWC is a specific design concrete with a minimum density of 1900 kg/m3 (DNV, 2007). Normally it consist of a mixture 4 components of coarse and fine aggregates (iron ore), portland cement and water in a certain proportions.

Iron ores are rocks and minerals from which metallic iron can be economically extracted. The ores are usually rich in iron oxides and vary in color from dark grey, bright yellow, or deep purple to rusty red. The iron itself is usually found in the form of magnetite (Fe_3O_4, 72.4% Fe), hematite (Fe_2O_3, 69.9% Fe), goethite (FeO(OH), 62.9% Fe), limonite ($FeO(OH)\cdot n(H_2O)$) or siderite ($FeCO_3$, 48.2% Fe) (Abdou, M.I., Abuseda, H., 2014). As the cost of iron ore increases, optimizing concrete mixture proportion for minimizing cost becomes more desirable. The company intends to substitute the iron ore fine aggregate with other minerals which is cheaper than the iron ore and widely availlable locally.

Indonesia is very rich of different minerals resulting from vulcanic activities. Rock density is very sensitive to the minerals that compose a particular rock type. Sedimentary rocks (and granite), which are rich in quartz and feldspar, tend to be less dense than volcanic rocks. Rocks of the same type can have a range of densities. This is partly due to different rocks of the same type containing different proportions of minerals. Granite, for example, can have a quartz content anywhere between 20 and 60 percent.

The densities of some minerals

Sandstone	2.2 - 2.8
Limestone	2.3 - 2.7
Marble	2.4 - 2.7

Andesite	2.5 - 2.8
Quartzite	2.6 - 2.8
Granite	2.6 - 2.7
Slate	2.7 - 2.8
Dolomite	2.8 - 2.9

Minerals that have density minimum of 2.6 is a candidate of substitute. The higher the density the better. However, the availability and the price to bring the mineral to the factory is much more important. The availability in this case is availability of correct size, correct amount, and correct lead time so that the production process of CWC can be performed appropriately. There are many minerals which technically suitable for substitute, however, commercially it is not availllable yet.

Iron sand from Lumajang which has a high content of ilmenite (Himando and Pintowantoro, 2013) are among of the minerals that are commercially availlable for substitute of fine aggregate (iron ore). The density of the iron sand is between 2.6 upto 3 kg/liter. The price of the material is significantly higher than crushed stone from Rembang due to transportation distance. For that reason the crushed stone which has density of 2.6 upto 2.9 kg/liter is choosen for the substitute of fine aggregate of iron ore. This substitution shall maintain the CTQ characteristics of the concrete within the acceptable limits of the industry. The main CTQ is concrete density and compressive strength.

The proportioning of concrete materials is carried out in a continuous batching process using belt conveyor system. The bulk materials are graded and stored in a separate bins. Each bins have an individual variable speed belt conveyor to control the speed of feeding and an adjustable gate to control the thickness of the material on the belt conveyor. From individual conveyor the material is fed into a main belt conveyor will transport all materials and feed it into the concrete mixer. The water is fed into the mixer through a piping and flow measuring system. The concrete mixture is then sprayed on pipe surfaces by high speed dual rubber rolls.

Fig. 1.1 Steel Pipe with Heavy Weight Concrete Coating

HWC coating is required to maintain subsea gas pipeline sitting on the sea-bed thanks to its negative bouyancy. The major critical to quality (CTQ) characteristics are density, compressive strength, water absorbtion, and impact resistant (DNV, 2007). The density is very important to get higher negative bouyancy and to improve on bottom stability. The compressive strength and impact resistance are important to overcome loads of installation or third party interference such as ship anchors or trawl board impacts (DNV, 2007).

To improve its tension strength to withstand the installation loads, one layer or more of steel reinforcement is placed within the concrete thickness. For small diameter (OD $\leq$ 14”) a galvanized wire mesh is used, while for outside diameter more than 14 inches either reinforcement steel cage or steel wire mesh or combination of both may be used.

HWC normally composed of coarse aggregate, fine aggregate, portland cement, and water (Abdou, M.I., Abuseda, H., 2014). They reported that hemetite iron ore and ilmenite ore have been successfully applied for HWC coating in Egypt. As ilmenite contain 30% of titanium, it was to precious for HWC coating so that it was replaced by hemetite iron ore.

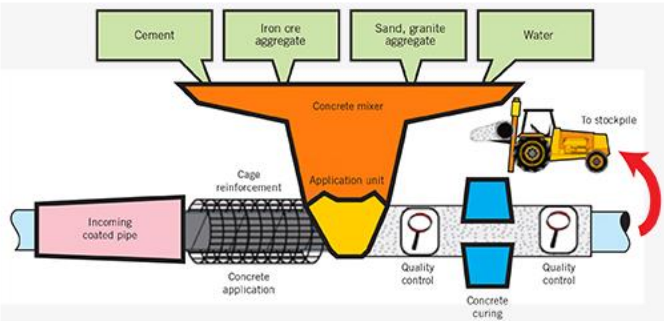

Fig. 1.2 Concrete weight coating processes
[Source: *http://www.brederoshaw.com/solutions/offshore/hevicote.html*]

The compressive strength of concrete is greatly depends on the water to cement ratio (w/c), cement, fine aggregate, and coarse aggregate proportions. Various numbers of w/c ratio were reported 0.8 (Bauw, 2000), and 0.4 (Afi Damaris, 2011), 0.45 – 0.6 (Onwuka, Prediction of Concrete Mix Ratio Using Modified Regression Theory, 2011). AWWA C-205 (AWWA, 2012) requires that the moisture content shall 7% by weight of the dry mix, and the cement to fine aggregate ratio shall be minimum 0.33 by weight. Several researches have been performed to investigate the relation between mix design of light weight concrete and the compressive strength.

The type of cement shall be considered when the design life of the pipeline is more than 20 years. The corrosion induced by chlorides from sea water may shorten the life time of the concrete. Girardi and Di Maggio (2011) reported that concrete shows extensive degradation when exposed to sulfate bearing solutions or polluted ground waters. The processes leading to corrosion in concrete sewer pipes are highly complex, still far from fully understood.

1.2 Statement of Problem

What is the optimum concrete constituents to get the best possible output in terms of density, compressive strength, and cost? This is done by optimising the mixture compositions by estimating different concrete compositions with different combinations of constituents and then to choose the best variants of these mixtures by comparing their density and compressive strength which will minimize the cost by Box-Behnken approach.

1.3 Research Objectives

The objective of this research is to find out the minimum cost of the proportion of the new design mix of HWC coating that meets the requirements.

1.4 Research Benefits

The major benefits of this research are encouraging the company of using a more precious natural resources (iron ore) efficiently, and improve competitive advantages of the company.

1.5 Definition

The scope of research is limited to the following:

1. The four components of mixture are as follow:
    a. Coarse aggregate : iron ore
    b. Fine aggregate : crushed stone or iron ore
    c. Portland cement
    d. Water
2. The CTQs of the heavy concrete to be considered are :
    a. Density
    b. Compression strength
    c. Cost
3. The coarse aggregate is iron ore size shall be 3/8” or more.
4. The fine aggregate is either iron ore or other minerals, with size 1/6” or less.

1.6 Writing Systematic

Chapters in this research are written in the following systematic:

- CHAPTER 1- INTRODUCTION

This chapter presents the background of the research, problem indentification, research objectives, research benefit, research scope and research outline.

- CHAPTER 2-LITERATURE REVIEW

This chapter draws on the various literatures and previous works on this subject, theoritical background, and standards that will be used as the basis for this research. Literatures used for this research are taken from books, journals and also related company’s SOP.

- CHAPTER 3 - RESEARCH METHODOLOGY

This chapter explains the research stages which cover the research program, type of data and their sources.

- CHAPTER 4- DATA ANALYSIS AND DISCUSSION

This chapter explains process of data collection which will be used for calculation. Data is collected from the execution of the experiment. This chapter describes how the data will be analyzed using MINITAB 17 and the result will be interpreted.

- CHAPTER 5- CONCLUSIONS AND RECOMMENDATIONS

This chapter presents the conclsion and recommendation following the analysis that is carried out in the previous chapter. This final chapter is expected to fulfill the objectives of the research. Suggestion for future research will also be introduced in this chapter.

CHAPTER 2
LITERATURE REVIEW

2.1 General Overview

Offshore gas development involves aggressive environment due to deep salt water, severity of prevailing climatic conditions imposed by high winds, strong seas and low temperature (Kyriakides and Edmundo Corona , 2007). Heavy aggregates of massive iron ore is utilized in the HWC mix used for concrete coating of submarine gas pipelines which will be immersed or laid on seabed under seawater to keep it firmly on the seabed not moving nor floating and to protect the pipes and its supplements against mechanical impacts.

The hostile environments and the currents on the sea floor call for coatings of sufficient weight to provide stability and of specific composition to prevent corrosion. These characteristics are provided by two layers of coating, anticorrosion coating and concrete coating. The concrete coatings to submarine pipelines are required to resist unique loads and are of unusual mix proportions. This gives rise to two problems when monitoring the quality of the coating. There is a risk of using inappropriate quality assurance techniques, or misinterpreting their results. The main components of the concrete mix are: cement, fine aggregates, heavy aggregates and mixing water. The cement shall be sulfate resisting Portland cement suitable for undersea uses in preparation of the concrete. Cement shall have a tricalcium aluminate content of not more than 3.5% and low alkali content less than 0.6% in order to attenuate the reactions of certain types of aggregates in marine environments. The type of cement shall be considered when the design life of the pipeline is more than 20 years.

The DNV standard (DNV, 2007) and ISO Standard (ISO:21809-5, 2010) requires that the concrete constituents and manufacturing method shall provide the following recommended minimum requirements to as-applied coating properties:

- minimum thickness: 40 mm,
- minimum compressive strength (i.e. average of 3 core specimens per pipe): 40 MPa (ASTM C39),
- maximum water absorption: 8% (by volume), and

- maximum water to cement ratio : 0,4 with minimum cement content shall be 400 kg/m3

To improve heavy concrete tension strength to withstand the installation loads, one layer or more of steel reinforcement is placed within the concrete thickness. The heavy aggregate is usually from iron ore or other type of heavy mineral. Abdou and Abuseda reported that hemetite iron ore and ilmenite ore have been successfully applied for HWC coating in Egypt (Abdou, M.I., Abuseda, H., 2014). As ilmenite contain 30% of titanium, it was too precious for HWC coating so that it was replaced by hemetite iron ore.

Several works have been done by previous researchers to investigate the relation of the design mix and the compresive strength of regular concrete. A mathematical method based on modified regression theory is formulated for the prediction of compressive strength was proposed by Onwuka et al (2011). Another work by Onwuka et al (2013) reported the development of computer programmes based on simplex and modified regression theories for designing concrete mixes to predict the compressive strength.

An optimization of mixture proportions of six components for high performance concretes using statistical experiment design and analysis method have been developed by Simon (2003). A further study of a mixture method and response surface method of experimental design of high performance concrete (HPC) was performed by Simon et al (1999). In this study Simon had three components of mixture; water, cement, and aggregate. Simon also reported his research which is intended to investigate the feasibility of using statistical experiment design (mixture approach) and analysis methods (factorial approach) to optimize concrete mixture proportions and to develop an internet-based computer program to optimize concrete mixture using these methods (Simon M. , 2003).

Optimization of mixture proportions for concrete pavements was reported by Rudy and Olek (2012). The influence of the amount and type of supplementary cementitious materials on selection of optimum proportions for concrete pavement mixtures was studied utilizing Response Surface Methodology (RSM) using 3 binders system.

A response surface methodology based experimental also carried out by Lotfy et al (2014) to model the influence of key parameters on the properties of LWSCC (Lightweight Self-Consolidating Concrete) mixtures developed with expanded clay. Three key design parameters were selected to derive mathematical models for evaluating fresh and hardened properties.

A study of concrete aggregate optimization was reported by Lindquist (2015). According to Lindquist to achieve an optimum gradation generally requires at least three differently sized aggregates. The methodology was using both the modified coarseness factor chart (MCFC) introduced by Shilstone and the percent retained chart.

Performance of concrete properties for different combined aggregate was reported by Ashraf and Noor (2011). It is reported that the concrete conpressive strength and workability are highly affected by its aggregate gradation. Moreover, concrete compressive strength can be increased more than 50% just by altering its aggregate gradation.

The influence of water on the performance of concrete was investigated by Hover who reported that the behaviour of concrete is intimately associated with water. Water is an essential element in most of the mechanism that degrade concrete properties over time (Hover, 2011).

The application of statistical models (response surface method) for proportioning lightweight self-consolidating concrete was reported by Lotfy, Hossain, and Lachemi (2014). Three key mix design parameters were selected to derive mathematical model for evaluating fresh and hardened properties.

Muthukumar et al. (2003) studied the optimization of mix proportions of silica aggregates for use in polymer concrete was attempted using Box-Behnken Design. High purity silica aggregates of six different standard particle sizes were chosen for the study. Void content of 54 statistically designed combinations were experimentally determined by adopting standard technique. Using Design Expert software the results were analyzed and an optimum composition having minimum void content was achieved. The optimum combination had a correlation coefficient of 0.95782 which proved the fitness of the selected model in analyzing the experimental data.

2.2 Introduction to Response Surface Methodology

The choice of an experimental design depends on the objectives of the experiment and the number of factors to be investigated:

a. Comparative objective

If we have one or several factors under investigation, but the primary goal of your experiment is to make a conclusion about one a-priori important factor, (in the presence of, and/or in spite of the existence of the other factors), and the question of interest is whether or not that factor is "significant", (i.e., whether or not there is a significant change in the response for different levels of that factor), then we have a comparative problem and we need a comparative design solution.

b. **Screening objective:**

The primary purpose of this experiment is to select or screen out the few important main effects from the many less important ones. These screening designs are also termed main effects designs.

c. Response Surface (method) objective:

The experiment is designed to allow us to estimate interaction and even quadratic effects, and therefore give us an idea of the (local) shape of the response surface we are investigating. For this reason, they are termed response surface method (RSM) designs. RSM designs are used to:

- Find improved or optimal process settings.
- Troubleshoot process problems and weak points.
- Make a product or process more robust against external and non-controllable influences. "Robust" means relatively insensitive to these influences.

d. Optimal fitting of a regression model objective:

If we want to model a response as a mathematical function (either known or empirical) of a few continuous factors and we desire "good" model parameter estimates (i.e., unbiased and minimum variance), then we need a regression design.

Response surface methods are used to examine the relationship between a response and a set of quantitative experimental variables or factors. These methods are often employed after a "vital few" controllable factors have been identified and it is required to find out the factor settings that optimize the response. Designs of this type are usually chosen when it is suspected that the response surface is curvature.

Response surface methods may be employed to:

- Find factor settings (operating conditions) that produce the "best" response
- Find factor settings that satisfy operating or process specifications

- Identify new operating conditions that produce demonstrated improvement in product quality over the quality achieved by current conditions
- Model a relationship between the quantitative factors and the response

Minitab provides two response surface designs: Central Composite Designs (CCD) and Box-Behnken Designs (BBD).

2.2.1 Central Composite Design (CCD)

The most commonly used response surface experimental design is central composite design. Central composite designs consist of a factorial or fractional factorial design with center points, augmented with a group of axial (or star) points that allow estimation of curvature. we can use a central composite design to:

- Efficiently estimate first- and second-order terms
- Model a response variable with curvature by adding center and axial points to a previously-run factorial design.

A central composite design consists of a "cube" portion made up of the design points from a factorial or fractional factorial design; 2K axial or "star" points, and center points (where K is the number of factors). Points on the diagram below represent the experimental runs that are performed in a 2-factor central composite design:

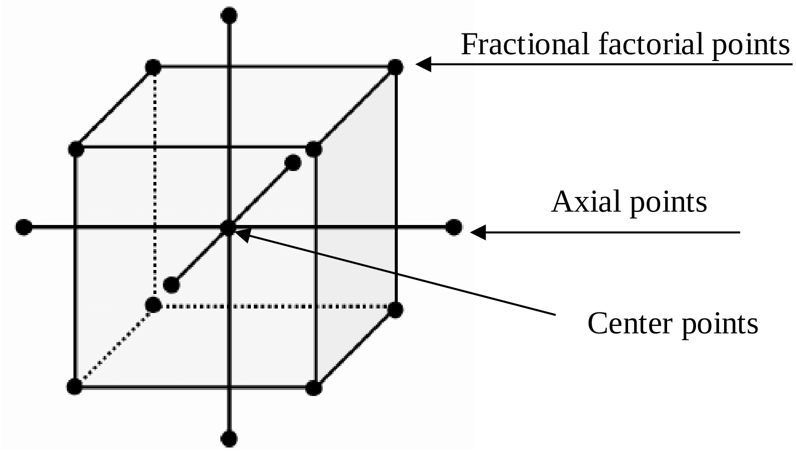

Fig. 2.1 Central Composite Design

Key features of this design include:

- Recommended for sequential experimentation since they can incorporate information from a properly planned two-level factorial experiment
- Allows for efficient estimation of quadratic terms in a regression model
- Exhibits the desirable properties of having orthogonal blocks and being rotatable or nearly rotatable.

2.2.2 Box-Behnken Design (BBD)

A Box-Behnken design is a three level design in which all the design points are either:

- at the center of the design
- centered on the edges of the cube, equidistant from the center

Additionally, the design points are never set at extreme (low or high) levels for all factors simultaneously. The diagram below represents a three factor design without center points. The points represent the experimental runs that are performed.

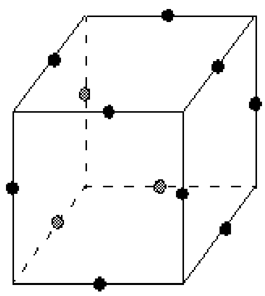

Fig. 2.2 Box-Behnken design

Key features of this design include:

- Allow efficient estimation of quadratic terms in a regression model
- Exhibits the desirable properties of having orthogonal blocks and being rotatable or nearly rotatable
- Usually consists of fewer design points and therefore are less expensive to run than central composite designs

- All design points fall within safe operating limits (within the nominal high and low levels) for the process

Muthukumar, et al. (2002) had applied the RSM-BBD approach on their research for optimization of mix proportions of silica aggregates for use in polymer concrete was attempted using statistical techniques. High purity silica aggregates of six different standard particle sizes were chosen for the study. Void content of 54 statistically designed combinations were experimentally determined by adopting standard technique. Using Design Expert software the results were analyzed and an optimum composition having minimum void content was achieved. The optimum combination had a correlation coefficient of 0.95782 which proved the fitness of the selected model in analyzing the experimental data.

2.3 Heavy Weight Concrete Coating System

The objectives of a concrete weight coating are to provide negative buoyancy to the pipeline, and to provide mechanical protection of the corrosion coating and linepipe during installation and throughout the pipeline's operational life. The concrete weight coating (thickness, strength, density, amount of reinforcement) shall be designed for the specific project; i.e. the actual installation, laying and operation conditions for the pipeline shall then be taken into consideration. For materials and application of concrete weight coating requirements in ISO 21809-5 shall apply with the additional and modified requirements. The following modification of acceptance criteria for inspections and tests during PQT shall apply:

- The thickness of the concrete coating shall not be less than 40 mm
- The minimum in-situ compressive strength of the concrete coating shall not be less than 40 MPa. The mean strength shall be calculated from compressive test results of three drilled cores obtained from one pipe, with no single test results less than 34 MPa.
- The minimum density shall be 3040 kg/m3.
- The concrete coating shall be reinforced by steel bars welded to cages or by wire mesh steel. The minimum percentage of the steel reinforcement shall be 0.5% circumferentially and 0.08% longitudinally of the cross-sectional area of the

concrete coating. The minimum diameter of circumferential cage reinforcement shall be 5 mm. The maximum spacing between circumferential and longitudinal cage reinforcement shall be 125 mm and 250 mm, respectively. The minimum diameter of wire mesh reinforcement shall be 2 mm. The minimum overlap of wire mesh reinforcement shall be 1.5 x distance between the wires or 25 mm (whichever is greater). Minimum concrete cover to the reinforcement shall be 15 mm for concrete thickness less or equal to 50 mm and minimum 20 mm for concrete thickness greater than 50 mm. The thickness of the concrete coating shall not be less than 40 mm.

All those standard requirements shall be maintained and fulfilled with the new concrete mixture design. Minerals that have density minimum of 2.2 is a candidate of substitute. The higher the density the better. However, the availability and the price to bring the mineral to the factory is much more important. The availability in this case is availability of correct size, correct, amount, and correct lead time so that the production process of CWC can be performed as per schedule.

2.4 Research Mapping

Several works have been done previosly with various materials, CTQ, and methods. Muthukumar et al (2003) have used Box-Behnken design of experiment to optimize 6 silica sizes for obtaining mixture with minimum voids. It was concluded that out of the six different particle sizes chosen for the study, only three of them were found to be sufficient for obtaining a mix with minimum void content. A full mapping of several previous researchs is presented in Table 2.1.

Tabel 2.2 Research Map

Author / Year	Title	Descriptions	Catagories	Results
Simon et al / 1999	Advances in Concrete Mixture Optimation	Research on mixture design of High Performance Concrete by Mixture Approach and RSM CCD.	HPC DOE RSM Mixture experiment	RSM can be used to determine the mixture of concrete that meet specification and satisfying specified constraints

Author / Year	Title	Descriptions	Catagories	Results
		The response are compresive strength, and cost	CTQ: compressive and cost	
Muthukumar et al / 2003	Optimization of mix proportions of mineral aggregates using Box-Behnken design of experiments	Optimization of 6 factors of silica sizes for concrete mixture using Box-Behnken design	DOE RSM Box-Benken Design Regression analysis CTQ: Minimum void	It was concluded that out of the six different particle sizes chosen for the study, only three of them were found to be sufficient for obtaining a mix with minimum void content.
Onwuka et al / 2011	Prediction of concrete mix ratios using modified regression theory	Using simplex lattice model of four component mixture and expanded Taylor's series compared with experimental method to predict the mix ratio and the compressive strength with mathematical model	LWC Mixture experiment Taylor's series mathematical model CTQ: Compressive	The mathematical model is confirmed by the experiment result
Rudy and Olek, 2012	Optimization of Mixture Proportions for Concrete Pavements—Influence of Supplementary Cementitious Materials, Paste Content and Aggregate Gradation.	The Response Surface Methodology (RSM) was utilized to design test matrices of concrete mixtures consisting of three binder systems: the fly ash system, the GGBFS system and the fly ash plus GGBFS system. For each binder system, the paste content varied from 21 to 25% by mixture volume.	LWC Multi components. Optimization. CTQ : compressive	The optimum composition of concrete mixtures was found to be 29% of fly ash and 22% of paste for the fly ash system, 37% of GGBFSand 23% of paste for the GGBFS system, and 15% of fly ash, 27% of GGBFS an 22% of paste for the ternary system.

Author / Year	Title	Descriptions	Catagories	Results
Vahidnia, A., 2012	Investigating the efect of changing in aggregation of stone materials containing high specific gravity with constant fineness modulus on penetration of chloride ion, compressive strength, and density of heavy concrete	Conventional mixture approach laboratory experimentation.	CTQ: Chloride penetration Compressive Density	The increase in compressive strength of SP 25-A to SP-25-D samples and SP 12.5-A to SP 12.5-D samples doesn't lead to same changes of the penetration of chloride ion. In general the unit volume weights of the concrete of SP 25 samples are more than SP 12.5 samples.
This research	Design Mix Optimization Of Heavy Concrete Coating Process At PT XYZ By Response Surface Methodology Box-Behnken Design	RSM with mixture experiment is used to find the optimum the mixture of HWC (Heavy Weight Concrete) consist of 4 components with 3 responses	CTQ : Density Compressive Cost	

CHAPTER 3
RESEARCH METHODOLOGY

This research is a design of experimental. The major factors that have a significant influences to the response have been identified by previous research and international standards and the main objective is yo minimize cost. For that reason Response Surface Methodology is choosen, and Box-Behken design is selected because this design require less sample with a good result.

3.1 Flowchart

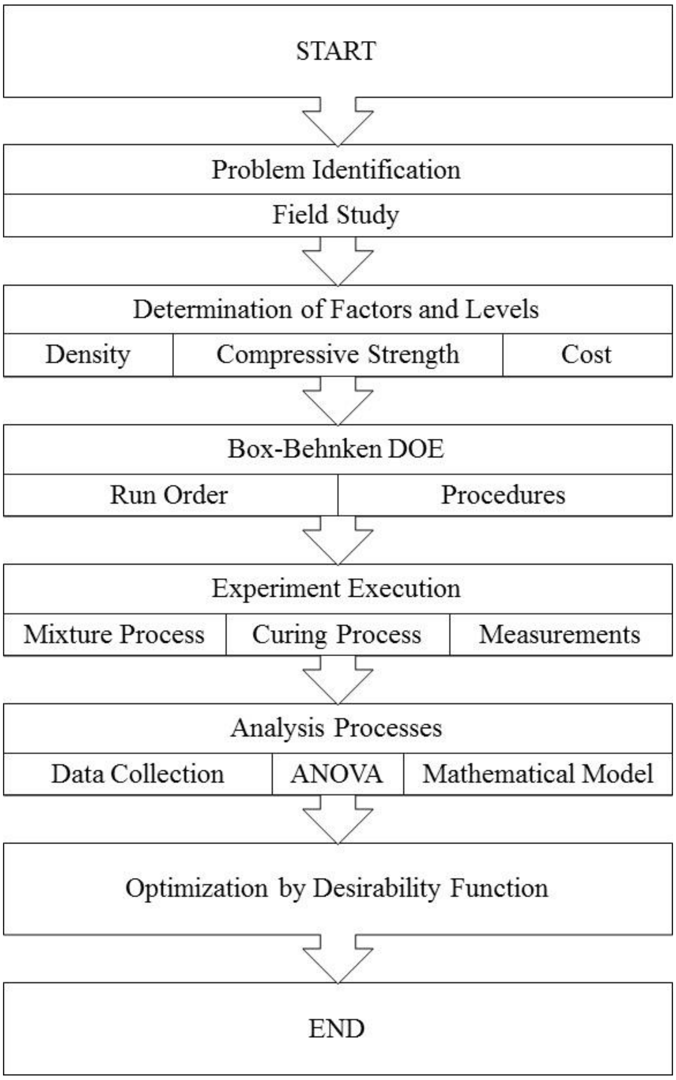

Fig. 3. 1 Flow Chart of Research Process

3.2 Problem Identification

Based on field and literature studies the CTQ of heavy concrete is affected by four factors :

1. Water
2. Portland Cement
3. Fine Aggregate
4. Coarse aggregate

For the purpose of this study all materials will be chosen from the one available at PT XYZ as follow:

- Water : potable water
- Portland Cement : The cement is type 2 produced by PT SEMEN TIGA RODA, CIBINONG. It shall comply with the requirements of ASTM C150.
- Fine Aggregate : The crushed stone is from Rembang 1 mining area, with size 1/6" or less
- Coarse aggregate : The iron ore for heavy aggregate is from Pelaihari mining site, South Kalimantan. It shall conform to ASTM C33. The coarse aggregate is iron ore size shall be 3/8" or more.

3.3 Experiment Design Details

Selecting an appropriate experiment design depends on several criteria, such as ability to estimate the underlying model, ability to provide an estimate of repeatability, and ability to check the adequacy of the fitted model. The "best" experiment design depends on the choice of an underlying model which will adequately explain the data. For this experiment, the following quadratic Scheffé polynomial was chosen as a reasonable model for each property as a function of the four components:

$$y = b_1X_1 + \ldots + b_4X_4 + b_{12}X_1X_2 + \ldots + b_{34}X_3X_4 + b_{11}X_1^2 + b_{22}X_2^2 + b_{33}X_3^2 + b_{44}X_4^2 + e \quad (3.1)$$

where :

X_1 = water proportion, X_2 = cement proportion, X_3 = fine aggregate proportion, X_4 = coarse aggregate proportion.

In the analysis of Response Surface Design, Minitab fits a typical model with main effects, two-factor interactions, and quadratic effects. If any of higher-order terms are not significant in the first analysis, they can be removed from the model until all remaining terms are signifucant or are required to maintain hieranchy (Sleeper, 2012). Then using the Minitab Response Optimizer, factor setting to maximize, minimize, or find a target value are easy to identify.

Based on the requirement of DNV-OSF-101 (DNV, 2007) and ISO 21809-5 (ISO:21809-5, 2010) it is determined that the levels of 4 (four) factors as follow in kilograms:

Factor 1 = X1 = water minimum 30 and maximum 110

Factor 2 = X2 = cement minimum 400, and maximum 992

Factor 3 = X3 = fine aggregate, minimum 812, and maximum 1596

Factor 4 = X4 = heavy aggregate, minimum 1290, and maximum 2494

Using MINITAB 17 we can compose a complete design of experiment as per Table 3.1

Tabel 3.2 Box-Behnken Design Of Experiment For 4 Factors 1 Replicate

RunOrder	StdOrder	PtType	Blocks	**X1**	**X2**	**X3**	**X4**
15	1	2	1	70	400	1596	1892
7	2	2	1	70	696	812	2494
5	3	2	1	70	696	812	1290
8	4	2	1	70	696	1596	2494
13	5	2	1	70	400	812	1892
24	6	2	1	70	992	1204	2494
1	7	2	1	30	400	1204	1892
16	8	2	1	70	992	1596	1892
23	9	2	1	70	400	1204	2494
21	10	2	1	70	400	1204	1290
2	11	2	1	110	400	1204	1892
25	12	0	1	70	696	1204	1892
26	13	0	1	70	696	1204	1892
11	14	2	1	30	696	1204	2494
20	15	2	1	110	696	1596	1892
27	16	0	1	70	696	1204	1892
14	17	2	1	70	992	812	1892
19	18	2	1	30	696	1596	1892
18	19	2	1	110	696	812	1892
4	20	2	1	110	992	1204	1892
17	21	2	1	30	696	812	1892
3	22	2	1	30	992	1204	1892
12	23	2	1	110	696	1204	2494
9	24	2	1	30	696	1204	1290
22	25	2	1	70	992	1204	1290
10	26	2	1	110	696	1204	1290
6	27	2	1	70	696	1596	1290

Source : Minitab 17

3.4 Experiment Execution Procedure

Before conducting the experiment, review the following guidelines and complete the appropriate activities:

1. Train individuals involved in the experiment : Because errors in the experimental procedures can invalidate the results of an experiment, all procedures should be carefully

documented and individuals trained on those procedures (Montgomery & Runger, 2011). Include the following:

- Specify how to measure the response and note any special techniques that may be required.
- Stipulate how to set factor levels. Make sure everyone understands how to set the factors at each level.
- Explain how to set up the equipment for runs. For example, each time the machine settings is changed, the machine shall be run at the new settings until it stabilizes before collecting the measurements for the experiment.
- Develop plans for troubleshooting. Communicate how to handle potential problems, such as missing measurements.
- Specify how to record special circumstances. Explain how to track any changes in conditions that may occur while the data is being collected.

2. Validate measurement system : to trust the experimental results, it is needed to verify that the measurement system is accurate. The measurement systems that are used both to measure the response and to set the factor levels should be verified.
3. If the experiments are part of a larger improvement project, such as a six sigma project, the measurement system for the response should have been validated previously. Make sure that the measurement system had been verified for the factors as well.
4. Check all design combinations. After the design is created, the actual combinations of factor settings for each experimental run need to be reviewed to make sure they are feasible and safe to run.
5. Perform trial runs. Performing trial runs before running an experiment is useful, if time and budget permits. Trial runs will allow to:
    - Assess the consistency of materials in the experiment.
    - Check the measurement systems for the experiment.
    - Test the experimental procedures and ensure that operators perform them correctly.
    - Check that the different combinations of factor levels can be run safely.
    - Obtain preliminary estimates of variation.

Based on the Box-Behnken design table, the experiment shall be executed sequentially in accordance with the run-order (Montgomery & Runger, 2011). The proportion limits of each factors shall be measured and controlled using appropriate tools and equipments.

For the purpose of this experiment each mixing shall be enough for making 3 (three) cube speciments of 100 mm x 100 mm x 100 mm. To speed up the curing period all specimens shall be steam cured for 18 hours. After 7 (seven) days cured the specimens shall be weighted and compressive test shall be performed. Weight dan compressive value data shall be recorded.

(1) Cube Mold (2) Analitical balance (3) Universal testing maschine

Fig. 3. 2 Standard Tool And Equipments

3.5 Data Analysis

The relationship between data (density and compressive values) as a response to the 4 (four) quantitative experimental variables (factors) will be analized using Response surface methods. The density response (Y1), the compressive strength response (Y2) and the combined response (Y3 = Y1 + Y2) will be analyzed and optimized. A matemathical regression model will be generated for each responses and its combination as a function of each factors. We want to find the factor settings that optimize the response. Each response will be plotted against X_3 (crushed stone) and X_4 (iron ore) while assume the other factors are constant. A minimum acceptable value for compressive strength is 40 MPa, and density 3040 kg/m3. The feasible factor space for the mixture experiment of four components can be determined. Cost analysis will be carried out to find out the minimum cost of the new mixture.

Using Analyze Response Surface Design from MINITAB 17 to fit a model to data collected using Box-Behnken, and choose to fit models with the following terms: linear terms, squared terms, interaction terms.

From the analysis of variance table we will use the p-values to determine which of the effects in the model are statistically significant. Typically we look at the interaction effects in the model first because a significant interaction will influence how we interpret the main effects.

3.6 Model Fitting

S, R^2, adjusted R, and predicted R obtained from the MINITAB data analysis are measures of how well the model fits the data. The fit is the predicted mean of the response at these variable settings.

From the regresion equation the fitted value can be calculated and the smaller the difference between the oberved value from the fitted value the better the model.

3.7 Optimization

Using Minitab's Response Optimizer we will identify the variable settings that optimize a single response or a set of responses. For multiple responses, the requirements for all the responses in the set must be satisfied.

CHAPTER 4
DATA AND ANALYSIS

Based on the data collected from the execution of the experiment, a matemathical model will be developed for the correlation between factors (water, cement, crushed stone, and iron ore) and responses (density, compressive strength). An optimization will then be performed based on the following criteria:

1. Minimum density = 3040 kg/m3
2. Compressive strength = 40 MPa

Both criterion are the the factors which fulfill the above mentioned criteria and have the lowest price will be choosen as an optimum solution.

4.1 Experiment Results

The experiment have been executed resulting 27 cube samples of the individual mix from 27 runs in accordance with the Box-Behnken design table. After the samples cured, the samples are weighed and the individual weight are recorded. For example, the weight of sample #1 = 3100 grams = 3,100 kilograms. The volume of the cubes is 0,1 x 0,1 x 0,1 m^3 = 0,001 m^3. The density of sample #1 = 3100 kg/m^3. After all the density of the samples are known, the sample is put on the universal testing machine in the same sequence as before. The compression test is done, and the compressive strength is recorded. For example sample number 1 has compressive strength of 42,0 MPa. A complete results of the test is presented on Table 4.1 where the responses are densities (Y_1) in Kilograms per cubic meter (kgs/m^3) and compressive strength (Y_2) in Mega Pascal (MPa). The combined response Y3 = Y1 + Y2 without unit is presented for optimization analysis purpose.

The table is then analyzed using statistics software MINITAB 17. Response Surface Regression with Backward Elimination of Terms is chosen. The result is presented and discussed in the following sections. A complete statistical results are presented on the exhibits.

Table 4.1 Experiment Results

Run Order	**Std Order**	**Pt Type**	**Blocks**	**X_1**	**X_2**	**X_3**	**X_4**	**Y_1**	**Y_2**	**Y3**
15	1	2	1	30	992	1.204	1.892	3100	42,0	3142,0
7	2	2	1	30	696	812	1.892	2000	32,2	2032,2
5	3	2	1	30	696	1.204	1.290	2500	30,2	2530,2
8	4	2	1	30	696	1.204	2.494	3100	32,8	3132,2
13	5	2	1	30	696	1.596	1.892	3200	28,8	3228,8
24	6	2	1	70	992	812	1.892	2200	44,2	2244,2
1	7	2	1	70	992	1.204	1.290	2800	38,8	2838,8
16	8	2	1	70	992	1.204	2.494	3200	46,2	3246,2
23	9	2	1	70	992	1.596	1.892	3320	46,2	3366,2
21	10	2	1	30	400	1.204	1.892	2400	26,0	2426,0
2	11	2	1	70	696	812	1.290	2000	34,2	2034,2
25	12	0	1	70	696	1.204	1.892	2900	32,8	2932,8
26	13	0	1	70	696	1.204	1.892	2880	33,2	2913,2
11	14	2	1	70	696	1.204	1.892	2920	32,2	2952,2
20	15	2	1	70	696	812	2.494	2500	30,8	2530,8
27	16	0	1	70	696	1.596	1.290	3200	30,2	3230,2
14	17	2	1	70	696	1.596	2.494	3320	37,6	3357,6
19	18	2	1	110	992	1.204	1.892	3100	44,2	3144,2
18	19	2	1	110	696	812	1.892	2400	42,0	2442,0
4	20	2	1	110	696	1.204	1.290	2600	34,0	2634,0
17	21	2	1	110	696	1.204	2.494	3320	44,0	3364,0
3	22	2	1	110	696	1.596	1.892	3240	38,2	3278,2
12	23	2	1	70	400	812	1.892	2000	32,0	2032,0
9	24	2	1	70	400	1.204	1.290	2300	24,8	2324,8
22	25	2	1	70	400	1.204	2.494	2900	32,2	2932,2
10	26	2	1	70	400	1.596	1.892	3200	30,2	3230,2
6	27	2	1	110	400	1.204	1.892	2600	44,2	2644,2

4.2 Fitting Full Quadratic Model for Density (Y1) and Compressive Strength (Y2)

The relation of density and compressive strength with its constituents (water, cement, crushed stone, and coarse aggregate) is analyzed with Minitab 17. The influences of each factors (terms) to the responses (Y1 and Y2) is analyzed using regression model and ANOVA. In the analysis of Response Surface Design, Minitab fits a typical model with main effects, two-factor interactions, and quadratic effects. Minitab provide options of methods for RSM analysis: forward selection, backward selection, forward and backward selection, and best subset regression. In this case Regression Model is carried out using Backward Selection whereby all terms are included in the initial run, and terms with the highest P-value which is not significant will be removed. The process of removing the worst remaining terms continues until the model stops getting better.

The backward selection process of Y1 versus X1, X2, X3, X4 (see Exhibit 1) required 10 steps to get all low P-values, while for Y2 required 7 steps, and for Y3 required 9 steps (Exhibit 11). It is very important to assess the model as a whole. Tabel 4.2 listing the statistical report of each steps. The detail report of the Response Surface Regression for Y1 see Exhibit 3.

Table 4.2 Model Summary of Backward Selection Steps of Y1

Steps	1	2	3	4	5
S	123,68	118,84	115,02	112,19	109,68
R-sq [%]	96,37	96,37	96,34	96,27	96,20
R-sq (adj) [%]	92,14	92,74	93,20	93,53	93,82
R-sq (pred) [%]	79,16	80,91	84,86	86,35	87,97
Mallows’ Cp	15,00	13,00	11,11	9,34	7,58
Steps	6	7	8	9	10
S	109,13	108,65	113,53	118,21	122,59
R-sq [%]	96,00	95,80	95,16	94,48	93,76
R-sq (adj) [%]	93,88	93,93	93,38	92,82	92,28
R-sq (pred) [%]	87,63	89,63	88,86	88,67	89,23
Mallows’ Cp	6,24	4,89	5,01	5,27	5,63

In Step 2 (Table 4.2), the term with the highest p-value 0,951 (term X4*X4) was removed, and the model getting better indicated by reducing the standard deviation S from 123,68 to 118,84. The smaller the value of S the better.

The coefficient of determination for the model R-sq or R2 is high (96,37%), which mean that 96,37% of variation explained by the model. The higher R-sq the better. On the step 2 the R-sq value not change, but the value of R-sq (adj) and R-sq (pred) is increasing from 92,14 to 82,74 for R-sq (adj) and 79,16 to 80,91 respectively so that removing X4*X4 made the model better.

R-sq (adj) includes an adjustment to R-sq which reduces the adjusted R-sq for every term removed from the model. This is a safeguard against over-fitting. A model with too many variables may have high R-sq, but no good at prediction. In general, the best model has the highest value of adjusted R-sq.

Mallows' Cp is an attempt to balance the risks of too many variables with the risks of too few variables (Sleeper, 2012). Mallows' Cp is a measure of goodness-of-prediction. The formula is: (SSEp / MSEm) - (n - 2p) where SSEp is SSE for the model under consideration, MSEm is the mean square error for the model with all predictors included, n is the number of observations, and p is the number of terms in the model, including the constant. In general, look for models where Mallows' Cp is small and close to p. A small Cp value indicates that the model is relatively precise (has small variance) in estimating the true regression coefficients and predicting future responses. Models poor predictive ability and bias have values of Cp larger than p (Minitab, 2010). According to Montgomerry (Montgomery & Runger, 2011) The regression equation that have neglicable bias will have values of Cp that close to p, while those with significant bias will have values of Cp that are significantly greater than p. This initial model has 15 terms so that p = 15.

The highest P-value in Step 2 is 0,742 belong to term X2*X3. This term is removed in Step 3. The S value is getting smaller, the R-sq (Adj) and R-sq (pred) are getting larger so that removing X2*X3 make the model better. Slight reduction of the coefficient of determination R-sq is still acceptable. This improvement continues in Step 4 by removing X1*X4, Step 5 (removing X1*X1), Step 6 (removing X2*X4), and Step 7 (removing X1*X2). However, on Step 8 (removing X1*X3) the model getting worse: S increase, R-sq, R-sq (adj) and R-sq (pred) are decreasing.

Starting from Step 8 upto Step 10 the model is getting worse and and worse. S increasing from the lowest 108,65 (Step 7) to 113,53 (Step 8), 118,21 (Step 9) and 122,69 (Step 10). R-sq decreasing from 95,8 (Step 7) to 95,16, 94,48, 93,76. R-sq (adj) decresing from 93,93 (Step 7) to 93,38, 92,82, 92,28. Having this situation it is concluded that statistically the best model for Y1 vs X1, X2, X3, X4 is the one from Step 7.

Table 4.3 Model Summary of Backward Selection Steps of Y2

Steps	1	2	3	4
S	2,33	2,24	2,16	2,10
R-sq [%]	93,82	93,82	93,81	93,70
R-sq (adj) [%]	86,60	87,63	88,51	89,08
R-sq (pred) [%]	64,54	68,00	71,48	73,88
Mallows' Cp	15,00	13,00	11,01	9,23
Steps	**5**	**6**	**7**	
S	2,09	2,12	2,24	
R-sq [%]	93,36	92,75	91,46	
R-sq (adj) [%]	89,20	88,91	87,66	
R-sq (pred) [%]	75,33	76,14	74,58	
Mallows' Cp	7,89	7,06	7,57	

Similarly for response Y2 (compressive strength) on Table 4.3. Step 2 to Step 6 greatly improve the selected model:

- S reduced from : 2.33 to 2,12
- R-sq : 93,82 to 92,75
- R-sq (Adj) : 86,60 to 88,91
- R-sq (pred) : 64,54 to 75,14

However, Step 7 (removing X1*X4) tends to make the Y2 model worst, i.e. S increase to 2,24157, R-sq decrease to 91,46, R-sq (Adj) to 87,66, and R-sq (pred) to 74,58. For that reason the backward selection of Y2 model is stopped at Step 6.

Similarly for response Y3 = Y1 + Y2 (see Exhibit 11), after step 7 the model is getting worse. For that reason the backward selection of Y3 model is ended at step 7. For further reference a complete analysis of Y3 is presented in Exhibit 11.

4.3 Final Selected Model

The final model to be selected and the ANOVA is presented at Exhibit 5 and Exhibit 6 for Density (Y1) and Compressive Strength (Y2) respectively. These model shall be assessed and evaluated with several relevant tests.

The Response Surface Regression Equation in Uncoded Units for model of Y1 is as follow:

$$Y1 = -3255 + 8{,}91\ X1 + 1{,}822\ X2 + 4{,}730\ X3 + 0{,}892\ X4 - 0{,}000839\ X2*X2 - 0{,}000918\ X3*X3 - 0{,}00574\ X1*X3 - 0{,}000403\ X3*X4 \quad (4.1)$$

The Regression Equation in Uncoded Units for Y2 is as follow:

$$Y2 = 51{,}6 + 0{,}004\ X1 - 0{,}0168\ X2 - 0{,}02254\ X3 - 0{,}01481\ X4 + 0{,}001422\ X1*X1 + 0{,}000044\ X2*X2 - 0{,}000338\ X1*X2 + 0{,}000077\ X1*X4 + 0{,}000011\ X3*X4 \quad (4.2)$$

4.4 Residual Plots

To assess and diagnose common regression problems it is a convenient way to have a graphical presentation. Figure 4.1 and Figure 4.2 provide a four-in-one residual plots of density response (Y1) and compressive strength response (Y2).

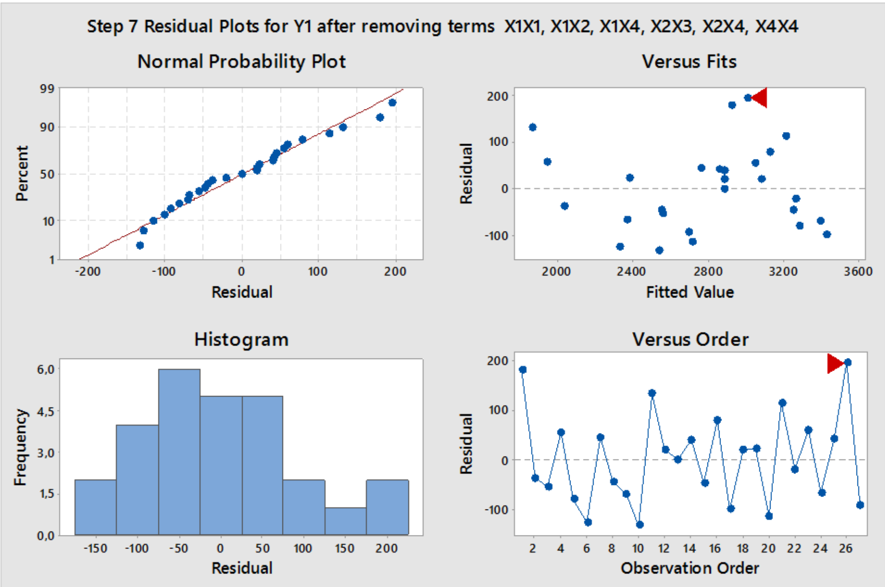

Fig. 4.1 Residual Plot of Y1

The normality test of the residual is on the top-left of Fig. 4.1. All data points is distributed around linear red line and it is proven to be normal. Because the number of data is more than 15 data points, normality is not an issue.

The distribution of residual against Observation Order shows a random distribution and no trend, shift, or cyclical pattern. There is one observation which has a large residual. It is observation no. 26 (red arrow) with residual 195,7. This large residual may be rooted from several sources, e.g. in accuracy of sample preparation because sequentially it is almost at the end of the experiment, variation of aggregate size distribution, etc. Due to time constraints that it is not possible to redo the experiment this data point is not replaced.

Large residual can be identified from Residuals vs Fits Plot. It is observation no. 26. No clusters, unusual X-values, or unequal variation observed.

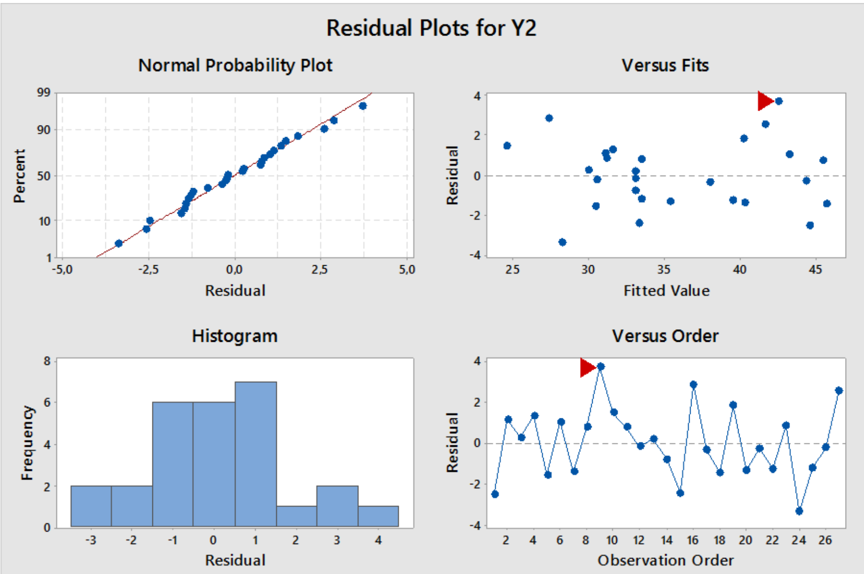

Fig. 4.2 Residual Plot of Y2

The case for compressive strength (Y2) is about the same as for density (Y1). The distribution of residual against Observation Order shows a random distribution and no trend, shift, or cyclical pattern. One data point has a large residual and is not well fit by the equation. This point is marked by red arrow on the top right and bottom right and is in row 9 of the worksheet. This large residual may be caused by several possible reasons, e.g.

measurement error, curing process error, etc. Due to time constraints that it is not possible to redo the experiment this data point is maintained.

The normality test of the residual is on the top-left of Fig. 4.2. and all data points is distributed along the linear line it is considered to be normal. Because the number of data is more than 15 data points, normality is not an issue.

4.5 Coefficient Determination Test

From Exhibit 5 and Exhibit 6, both models can be summrized as follow:

Table 4.4 Coefficient of Determination of Final Model

	S	R-sq	R-sq (Adj)	R-sq (pred)
Y1	108,65	95,80%	93,93%	89,63%
Y2	2,12	92,75%	88,91%	76,14%

The value of coefficient determinations R-sq for both density and compresive strength are above 90%, which mean that the percentage of variation explained by the models is 96,8% and 92,75% respectively so that both model pass the coefficient of determination test requirement.

4.6 Test of Coefficient of Regression

This test is carried out based on the following hypotheses at $\alpha = 0{,}05$:

H_0: Every β_i does not affect the response $(\beta_1 = \beta_2 = ... = \beta_k = 0)$

H_1: $\beta_i \neq 0$ for every i

Table 4.5 P-value From ANOVA Results

Model	Density (Y1)	Compressive Strength (Y2)
Regression	0,000	0,000
Linear	0,000	0,000
Quadratic	0,010	0,001
Interaction	0,081	0,002

This test to evaluate the influence of each factors in the model. The interaction between factors shall be evaluated first because interaction may influence other factors (Kuehl, 2000). Table 4.5 shows that the P-value of interaction for Y1 is greater than 0,05 so that H_0 fail to be rejected, it may be interpreted that interaction between factors may have influence to the density response but the influence not significant statistically. Although the interaction statistically has no significant affect but it is decided to maintain in the model because eliminating it will make the model getting worst as explained in Section 4.2.

Meanwhile P-value of interaction for Y2 is less than 0,05, so that H_0 shall be rejected. Meaning that interaction between water, cement, crushed stone, and iron ore coarse aggregate have statistically significant influence to compressive strength of the concrete.

The P-values of Regression, Linear, and Quadratic models are less than 0,05 so that the null hypotheses shall be rejected and conclusion can be drawn that those models have effects to density and compressive strength.

Table 4.6 Coded Coefficient of ANOVA Report for Y1

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	2880,6	36,2	79,54	0,000	
X1	80,0	31,4	2,55	0,020	
X2	193,3	31,4	6,16	0,000	1,00
X3	531,7	31,4	16,95	0,000	1,00
X4	245,0	31,4	7,81	0,000	1,00
X2*X2	-73,5	42,9	-1,71	0,104	1,04
X3*X3	-141,0	42,9	-3,28	0,004	1,04
X1*X3	-90,0	54,3	-1,66	0,115	1,00
X3*X4	-95,0	54,3	-1,75	0,097	1,00

From the above table there are 3 terms which have P-value greater than 0,05, i.e. X2*X2, X1*X3, and X3*X4 but removing it from the model only make it getting worse so that it is considered to maintained in the model.

Table 4.7 Coded Coefficient of ANOVA Report for Y2

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	33,000	0,708	46,59	0,000	
X1	4,550	0,613	7,42	0,000	1,00
X2	6,017	0,613	9,81	0,000	1,00
X3	-0,350	0,613	-0,57	0,576	1,00
X4	2,617	0,613	4,27	0,001	1,00
X1*X1	2,275	0,840	2,71	0,015	1,04
X2*X2	3,825	0,840	4,55	0,000	1,04
X1*X2	-4,00	1,06	-3,77	0,002	1,00
X1*X4	1,85	1,06	1,74	0,100	1,00
X3*X4	2,70	1,06	2,54	0,021	1,00

From Table 4.7 there are two terms which have P-value greater than 0,05, i.e. X3 and X1*X4. The same condition with before those terms are maintained in the model because removing them will make the model getting worse.

4.7 Contour Plot

For the contour plot of Y1 against X3, X4 is made by setting X1 and X2 constant. In this case X1 = 110 and X2 = 992. The contour plot of Y1 is presented on Fig. 4.1

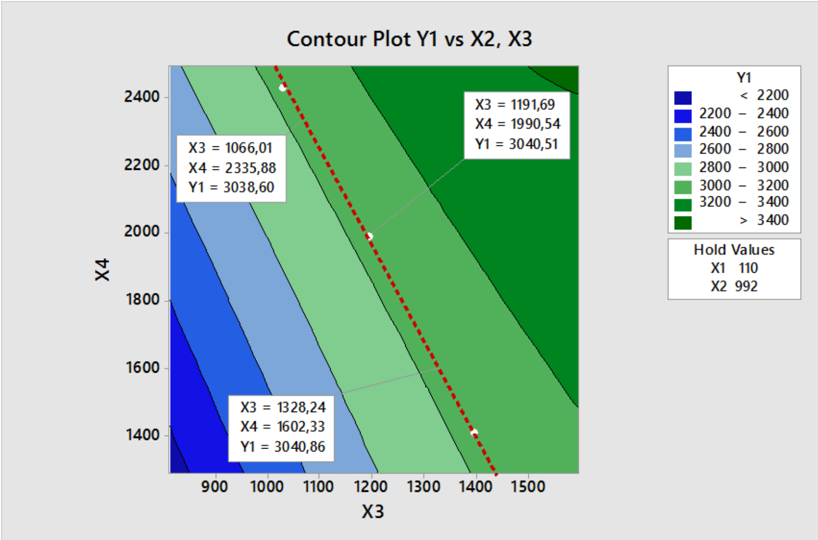

Fig. 4.3 Contour Plot of Y1 vs X3 and X4 at X1 = 110 and X2 = 992 With Red Line as a Constant Value of Density 3040 Kg/m3

In the contour plot, a constant density line can be drawn against X3 and X4. The feasible space solution for density equal or greater than 3040 kg/m3 is from the red line to the upper right area of the contour plot. This area is also presented in Figure 4.2.

In Figure 4.3 a contour plot of compressive strength against X3 and X4 with X1 = 110 and X2 = 992 is presented. A feasible space solution for minimum compresive strength of 40 MPa is from redline to the upper right area of the plot.

Combining Fig. 4.1 and Fig. 4.3 will give visual graphical idea how a feasible space solution which fulfill both requirements of minimum density 3040 kgs/m3 and minimum compressive strength of 40 MPa. The feasible space salution in this case is a possible design mix which statistically may produce concrete whose density $\geq$ 3040 kg/m3 and compressive strength of 40 MPa (minimum).

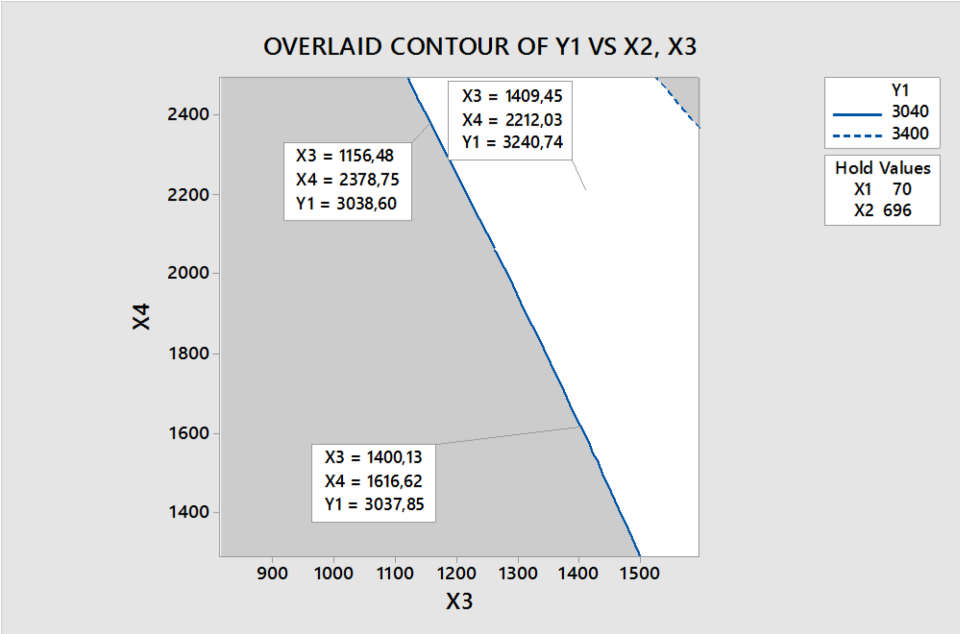

Fig. 4.4 Contour Plot of Y1 vs X3 and X4 at X1 = 110 and X2 = 992 With Red Line as a Constant Value of Density 3040 Kg/m3

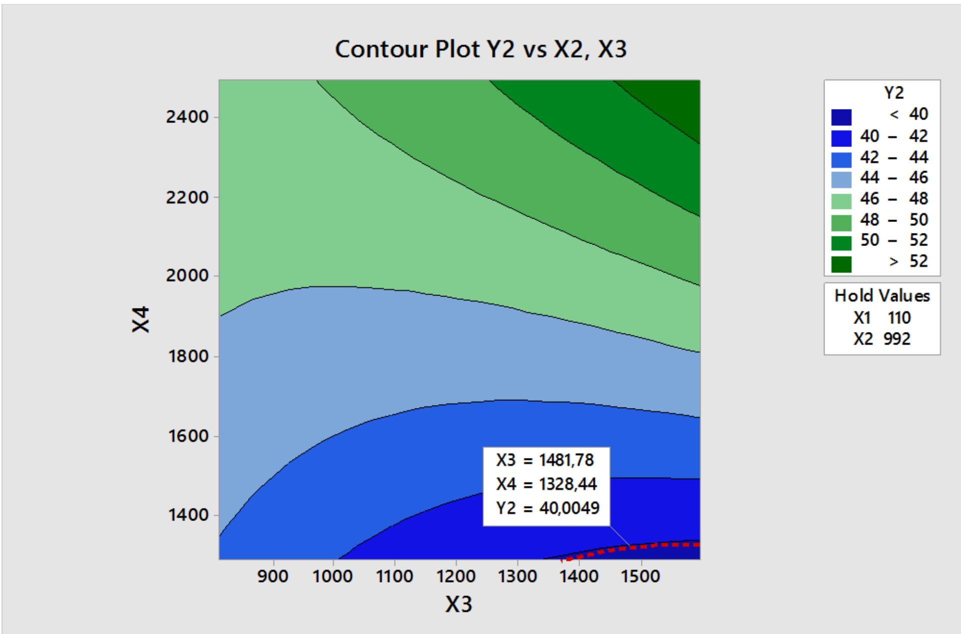

Fig. 4.5 Contour Plot of Y2 vs X3 and X4 at X1 = 110 and X2 = 992 With Red Line as a Constant Value of Compressive Strength 40 MPa.

Superimposing Fig. 4.3 over Fig. 4.1, we can find a joint feasible space solution for Y1 and Y2 graphically (Fig. 4.4). From this picture four (4) data points (design mixes) will be taken for optimization.

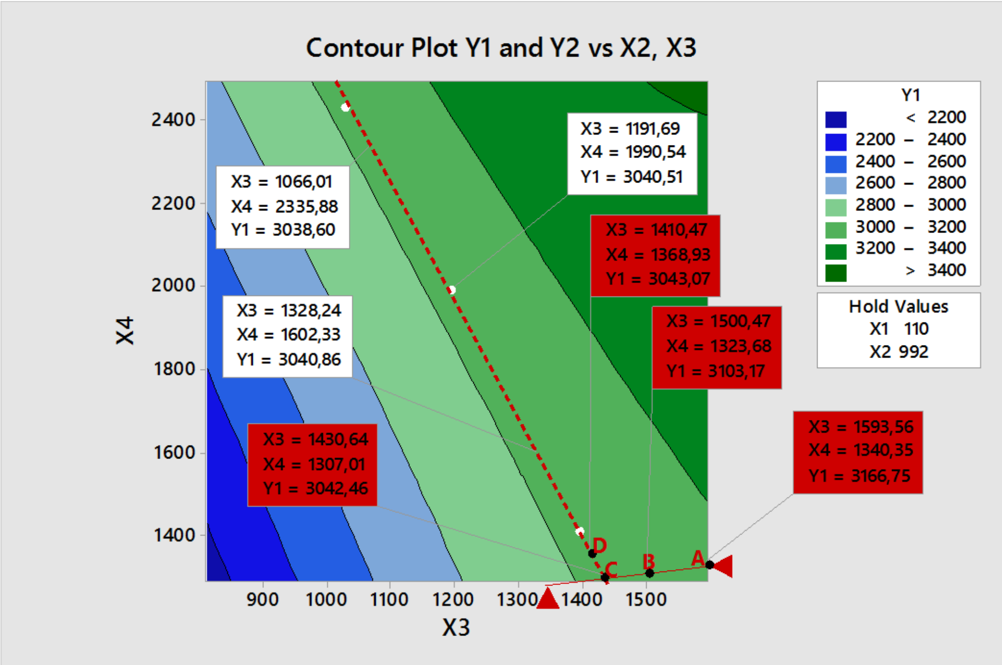

Fig. 4.6 Superimposed Contour Plots

Table 4.8 Four Data Points (Design Mixes) From the Feasible Area

Points	X1	X2	X3	X4	Y1	Y2
A	110	992	1593,56	1340,35	3166	40
B	110	992	1500,47	1323,68	3103	40
C	110	992	1430,64	1307,01	3042	40
D	110	992	1410,47	1368,93	3042	40

4.8 Surface Plots

Surface plots can be constructed by Minitab to give an easy way to evaluate the model graphically.

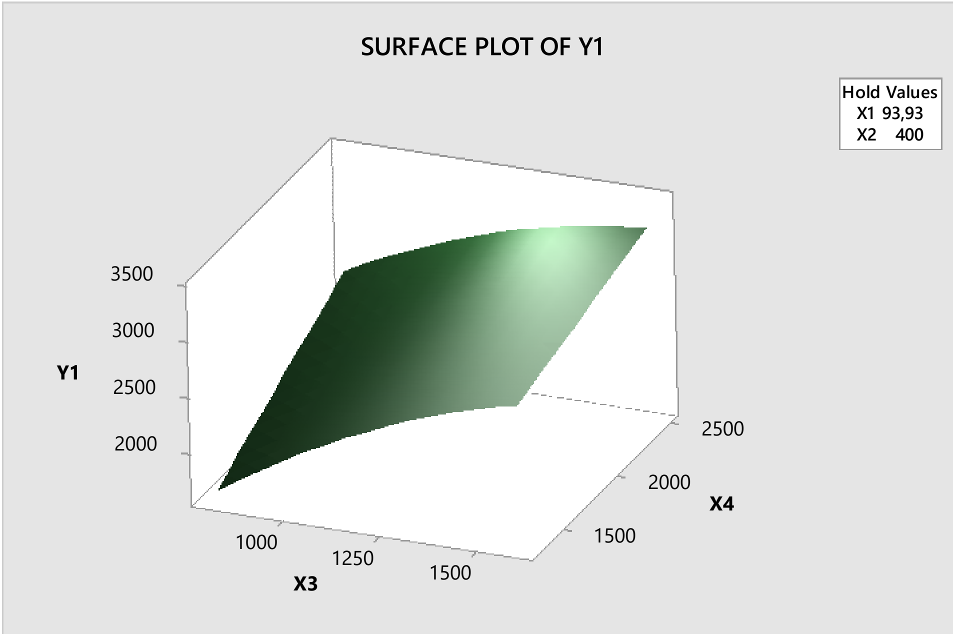

Fig. 4.7 Surface Plot of Y1

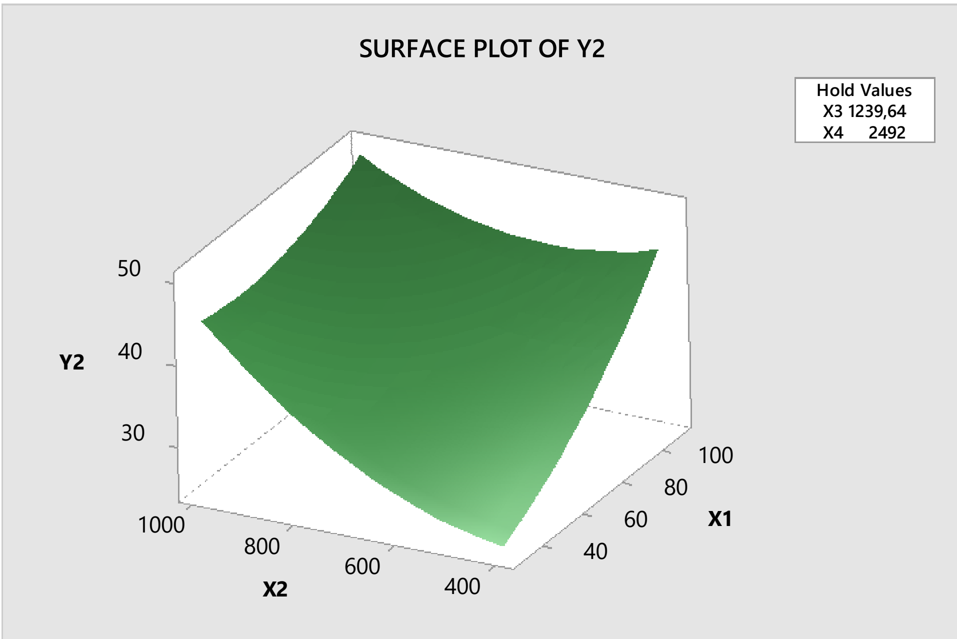

Fig. 4.8 Surface Plot of Y2 vs X3, X4

4.9 Response Optimizer for Y1 and Y2

Use response optimization to help identify the combination of input variable settings that jointly optimize Y1 and Y2 responses. Joint optimization must satisfy the requirements for Y1 and Y2 responses in the set, i.e. minimum 3040 kg/m3 and minimum 40 MPa respectively, which is measured by the composite desirability. Desirability assess how well a combination of input variables satisfies the goals you have defined for the responses. Individual desirability (d) evaluates how the settings optimize a single response; composite desirability (D) evaluates how the settings optimize a set of responses overall. Desirability has a range of zero to one. One represents the ideal case; zero indicates that one or more responses are outside their acceptable limits.

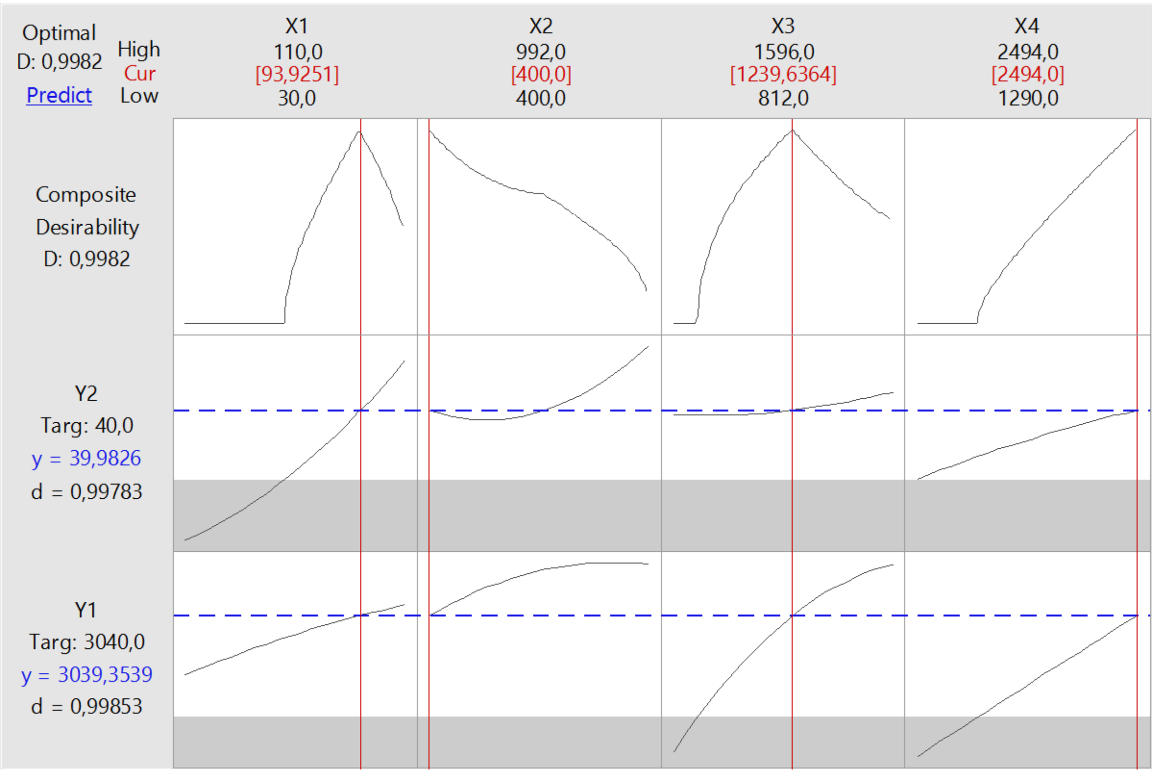

Fig. 4.9 Combined Response Optimizer Plot For Density and Compressive Strength at Target Values of Density 3040 kg/m3 and Compressive Strength of 40 MPa.

According to Fig. 4.9 the join optimum factors (design mix) which the responses fulfill the minimum requirements of density 3040 Kg/m3 and compressive strength 40 MPa and with composite desirability 0,9982 are as follow:

X1 = 93,92 X2 = 400 X3 = 1239,64 X4 = 2494,0

Table 4.9 Response Optimization: Y1 and Y2

Parameters

Response	Goal	Lower	Target	Upper	Weight	Importance
Y2	Target	32	40	48	1	1
Y1	Target	2600	3040	3400	1	1

Solution

Solution	X1	X2	X3	X4	Y2 Fit	Y1 Fit	Composite Desirability
1	93,9251	400	1239,64	2494	39,9826	3039,35	0,998178

Multiple Response Prediction

Variable	Setting
X1	93,9251
X2	400
X3	1239,64
X4	2494

Response	Fit	SE Fit	95% CI	95% PI
Y2	39,98	2,08	(35,45; 44,51)	(33,17; 46,80)
Y1	3039	110	(2800; 3279)	(2679; 3400)

According to the response optimizer of Y3 = Y1 + Y2 in Fig. 4.10, the optimum solution is as follow:

X1 = 71,1; X2 = 717,1; X3 = 1270,6; X4 = 2034,9

In this case the optimum value will give a minimum value of Y3 = 3080, however we do not certain what is the individual values of Y1 and Y2.

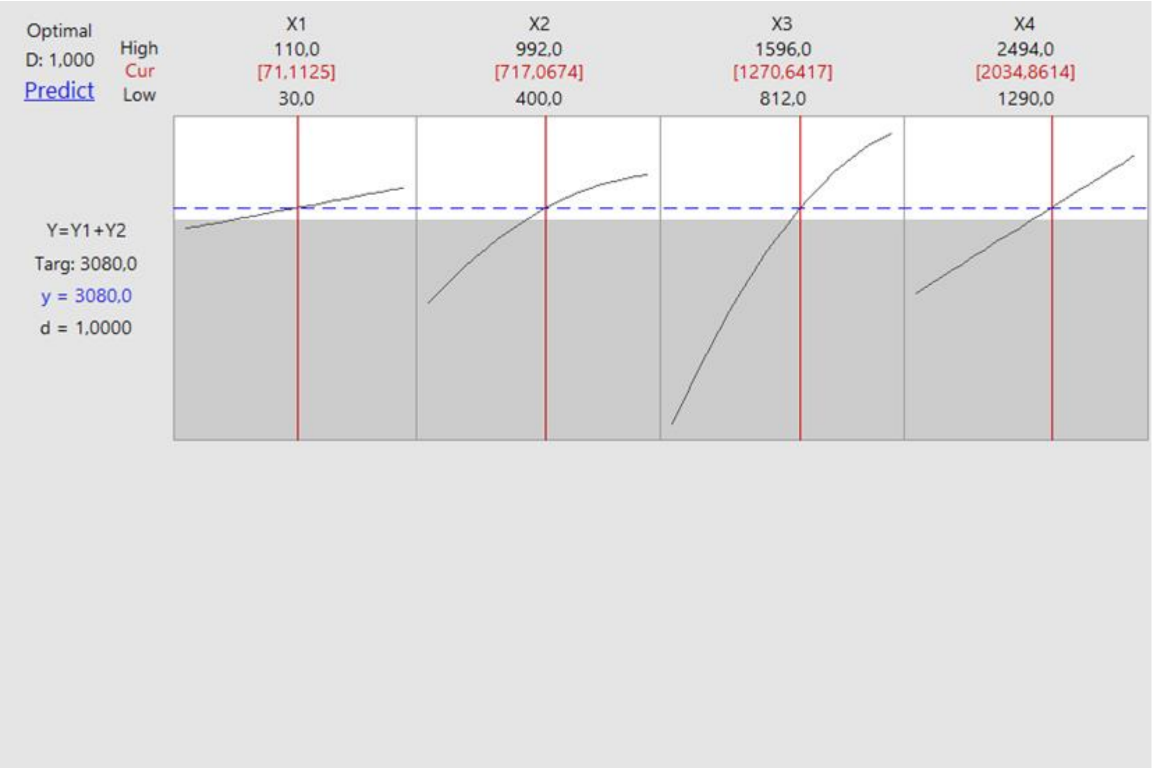

Fig. 4.10 Response Optimizer Plot For Y3 = Y1 + Y2 at Target Values of Density (Y1) 3040 kg/m3 and Compressive Strength of 40 MPa (Y2)

4.10 Cost Optimization

Cost optimization is based on the design mixes collected from two methods of optimization: joint optimization plot of Y1 and Y2 and optimization plot of Y3.

The cost calcultions are based on the unit price of materials are as follow:

P_{X1} = 0,6 USD/Ton; P_{X2} = 104 USD/Ton; P_{X3a} = 20 USD/Ton; and P_{X4} = 80 USD/Ton.

Method 1 :

X1 = 93,92 X2 = 400 X3a = 1239,64 X4 = 2494,0

Total cost = 93,92 x 0,6 + 400 x 104 + 1239,64 x 20 + 2494,0 x 80 = 265.969,16 USD

Total weight of mix = X1 + X2 + X3 + X3a + X4 = 4227,6 tons

Cost per unit weight of heavy weight concrete = 265.969,16/4227,6 USD/Tons = 62,91 USD/Ton

Method 2 :

X1 = 71,1; X2 = 717,1; X3 = 1270,6; X4 = 2034,9

Total cost = 71,1 x 0,6 + 717,1 x 104 + 1270,6 x 20 + 2034,9 x 80 = 262.825,06 USD
Total weight of mix = X1 + X2 + X3 + X3a + X4 = 4093,7 tons
Cost per unit weight of heavy weight concrete = 262.825,06 /4093,7 USD/Tons = 64,20 USD/Ton

The unit cost of materials are collected at the time of writing from the purchasing department of PT XYZ. The consumption of materials is collected from production engineering of PT XYZ. Cost calculation example and cost calculation table is presented in Exhibit 8. Among of two methods it is proven that data point # 1 gives the lowest total cost of material. This design mix consist of :

- Water = 93,92 liters
- Cement = 400 kgs
- Crushed stone = 1239,64 kgs
- Coarse aggregate = 2494,0 kgs

The total cost of the material following the most optimum design is 62,91 USD/Ton.

4.11 Improvement

Evaluating the current states of concrete coating production practice, there is potential improvement can be made out of this research. The unit cost of material for one ton concrete production using the existing material with fine aggregate of iron ore is 77,7 USD (see Exhibit 10). A potential improvement from the use of crushed stone to substitute fine iron ore are: (77,7 – 62,91) x 100% / 77,7 = 19 %

It should be noted that this experiment have been designed with some assumptions and exclutions. Validation shall be required to investigate the correctness between the design and the actual. This validation is not yet included in this research.

Based on the problem statement “What is the optimum concrete constituents to get the best possible output in terms of density, compressive strength, and cost?”, the answer is method 1.

Concrete mixture involve a chemical reaction which the result is depend not only the constituents but also the reaction temperature which is not considered in this research. The percentage of aggregate sizes (sieve analysis) may also have influences to the properties of the concrete which also excluded from this research.

CHAPTER 5
CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

1. The optimum design mix that produce concrete with minimum density of 3040 kg/m3 and compressive strength of 40 MPa with the lowest cost of materials shall consist of :
   - water (93,9 liters) or 0,07 by volume
   - cement (400 kgs) or 0,10 by volume
   - crushed stone (1239,6 kgs) or 0,36 by volume
   - coarse aggregate (2494 kgs) or 0,47 by volume
2. The total cost of the material following the most optimum design is 62,91 USD/Ton.
3. There is a potential improvement or saving of 19 % from the current state based on the optimized design mix from this research.
4. The mathematical model of the density response and compressive strength response are as follow:

Density = -3255 + 8,91 Water + 1,822 Cement + 4,730 CrushedStone + 0,892 IronOre - 0,000839 Cement^2- 0,000918 CrushedStone^2- 0,00574 Water*CrushedStone - 0,000403 CrushedStone*IronOre

Compressive Strength = 51,6 + 0,004Water - 0,0168Cement - 0,02254 CrushedStone - 0,01481 IronOre + 0,001422 Water^2 + 0,000044 Cement^2- 0,000338 Water*Cement + 0,000077 Water*IronOre + 0,000011 CrushedStone*IronOre

5.2 Recommendations

1. The effect of aggregate gradations and mixture temperature is not included in this research. A more detail research including those factors is recommended.
2. The effect of factors under consideration to the impact and shear properties of concrete are not studied. This poperties is important for the integrity of concrete coated linepipe during installation and operation. This is also recommended for further study.

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Exhibit 1 Result of Experiments

Run Order	Std Order	PtType	Blocks	X1	X2	X3	X4	Y1	Y2	Y3=Y1+Y2
15	1	2	1	30	992	1.204	1.892	3.100	42,0	3.142,0
7	2	2	1	30	696	812	1.892	2.000	32,2	2.032,2
5	3	2	1	30	696	1.204	1.290	2.500	30,2	2.530,2
8	4	2	1	30	696	1.204	2.494	3.100	32,8	3.132,8
13	5	2	1	30	696	1.596	1.892	3.200	28,8	3.228,8
24	6	2	1	70	992	812	1.892	2.200	44,2	2.244,2
1	7	2	1	70	992	1.204	1.290	2.800	38,8	2.838,8
16	8	2	1	70	992	1.204	2.494	3.200	46,2	3.246,2
23	9	2	1	70	992	1.596	1.892	3.320	42,4	3.362,4
21	10	2	1	30	400	1.204	1.892	2.400	26,0	2.426,0
2	11	2	1	70	696	812	1.290	2.000	34,2	2.034,2
25	12	0	1	70	696	1.204	1.892	2.900	32,3	2.932,3
26	13	0	1	70	696	1.204	1.892	2.898	33,2	2.931,2
11	14	2	1	70	696	1.204	1.892	2.902	32,2	2.934,2
20	15	2	1	70	696	812	2.494	2.500	30,8	2.530,8
27	16	0	1	70	696	1.596	1.290	3.200	30,2	3.230,2
14	17	2	1	70	696	1.596	2.494	3.320	37,6	3.357,6
19	18	2	1	110	992	1.204	1.892	3.100	44,2	3.144,2
18	19	2	1	110	696	812	1.892	2.400	42,0	2.442,0
4	20	2	1	110	696	1.204	1.290	2.600	34,0	2.634,0
17	21	2	1	110	696	1.204	2.494	3.320	44,0	3.364,0
3	22	2	1	110	696	1.596	1.892	3.240	38,2	3.278,2
12	23	2	1	70	400	812	1.892	2.000	32,0	2.032,0
9	24	2	1	70	400	1.204	1.290	2.300	24,8	2.324,8
22	25	2	1	70	400	1.204	2.494	2.900	32,2	2.932,2
10	26	2	1	70	400	1.596	1.892	3.010	30,2	3.040,2
6	27	2	1	110	400	1.204	1.892	2.600	44,2	2.644,2

Notes: Y1 = Density [kgs/m3]

Y2 = Compressive Strength [MPa]

Y3 = Y1 + Y2

Exhibit 2 Results of Real Density Measurements

Materials	Density [Kgs/m3]
Cement	3150
Coarse aggregate (Iron ore)	4000
Fine aggregate (Iron ore)	3000
Crushed stone	2640

Exhibit 3 Response Surfae Regression Model Y1 vs X1, X2, X3, X4

Backward Elimination of Terms

Candidate terms: X1; X2; X3; X4; X1*X1; X2*X2; X3*X3; X4*X4; X1*X2; X1*X3; X1*X4; X2*X3; X2*X4; X3*X4

	---Step 1---		---Step 2---		---Step 3---		---Step 4---	
	Coef	P	Coef	P	Coef	P	Coef	P
Constant	2900,0		2897,0		2897,0		2897,0	
X1	80,0	0,045	80,0	0,036	80,0	0,030	80,0	0,026
X2	193,3	0,000	193,3	0,000	193,3	0,000	193,3	0,000
X3	531,7	0,000	531,7	0,000	531,7	0,000	531,7	0,000
X4	245,0	0,000	245,0	0,000	245,0	0,000	245,0	0,000
X1*X1	-25,8	0,638	-24,7	0,619	-24,7	0,607	-24,7	0,597
X2*X2	-80,8	0,157	-79,7	0,124	-79,7	0,112	-79,7	0,102
X3*X3	-148,3	0,017	-147,2	0,010	-147,2	0,007	-147,2	0,006
X4*X4	-3,3	0,951						
X1*X2	-50,0	0,435	-50,0	0,415	-50,0	0,399	-50,0	0,387
X1*X3	-90,0	0,171	-90,0	0,154	-90,0	0,140	-90,0	0,129
X1*X4	30,0	0,636	30,0	0,622	30,0	0,610		
X2*X3	-20,0	0,752	-20,0	0,742				
X2*X4	-50,0	0,435	-50,0	0,415	-50,0	0,399	-50,0	0,387
X3*X4	-95,0	0,150	-95,0	0,134	-95,0	0,121	-95,0	0,111

S	123,682	118,849	115,024	112,198
R-sq	96,37%	96,37%	96,34%	96,27%
R-sq(adj)	92,14%	92,74%	93,20%	93,53%
R-sq(pred)	79,16%	80,91%	84,86%	86,35%
Mallows’ Cp	15,00	13,00	11,11	9,34

	---Step 5----		-----Step 6----		-----Step 7----		-----Step 8----	
	Coef	P	Coef	P	Coef	P	Coef	P
Constant	2880,6		2880,6		2880,6		2880,6	
X1	80,0	0,022	80,0	0,021	80,0	0,020	80,0	0,025
X2	193,3	0,000	193,3	0,000	193,3	0,000	193,3	0,000
X3	531,7	0,000	531,7	0,000	531,7	0,000	531,7	0,000
X4	245,0	0,000	245,0	0,000	245,0	0,000	245,0	0,000
X1*X1								
X2*X2	-73,5	0,109	-73,5	0,106	-73,5	0,104	-73,5	0,118
X3*X3	-141,0	0,005	-141,0	0,005	-141,0	0,004	-141,0	0,005
X4*X4								
X1*X2	-50,0	0,375	-50,0	0,372				
X1*X3	-90,0	0,120	-90,0	0,117	-90,0	0,115		
X1*X4								
X2*X3								
X2*X4	-50,0	0,375						
X3*X4	-95,0	0,102	-95,0	0,100	-95,0	0,097	-95,0	0,111

S	109,685	109,139	108,652	113,530
R-sq	96,20%	96,00%	95,80%	95,16%
R-sq(adj)	93,82%	93,88%	93,93%	93,38%
R-sq(pred)	87,97%	87,63%	89,63%	88,86%
Mallows’Cp	7,58	6,24	4,89	5,01

	-----Step 9----		----Step 10----	
	Coef	P	Coef	P
Constant	2841,3		2841,3	
X1	80,0	0,030	80,0	0,035
X2	193,3	0,000	193,3	0,000
X3	531,7	0,000	531,7	0,000
X4	245,0	0,000	245,0	0,000
X1*X1				
X2*X2				
X3*X3	-126,3	0,012	-126,3	0,015
X4*X4				
X1*X2				
X1*X3				
X1*X4				
X2*X3				
X2*X4				
X3*X4	-95,0	0,124		

S	118,217	122,592
R-sq	94,48%	93,76%
R-sq(adj)	92,82%	92,28%
R-sq(pred)	88,67%	89,23%
Mallows' Cp	5,27	5,63

α to remove = 0,05

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	5	4744067	948813	63,13	0,000
Linear	4	4637667	1159417	77,15	0,000
X1	1	76800	76800	5,11	0,035
X2	1	448533	448533	29,84	0,000
X3	1	3392033	3392033	225,70	0,000
X4	1	720300	720300	47,93	0,000
Square	1	106401	106401	7,08	0,015
X3*X3	1	106401	106401	7,08	0,015
Error	21	315607	15029		
Lack-of-Fit	19	314807	16569	41,42	0,024
Pure Error	2	800	400		
Total	26	5059674			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
122,592	93,76%	92,28%	89,23%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	2841,3	31,7	89,76	0,000	
X1	80,0	35,4	2,26	0,035	1,00
X2	193,3	35,4	5,46	0,000	1,00
X3	531,7	35,4	15,02	0,000	1,00
X4	245,0	35,4	6,92	0,000	1,00
X3*X3	-126,3	47,5	-2,66	0,015	1,00

Regression Equation in Uncoded Units

Y1 = -1348 + 2,000 X1 + 0,653 X2 + 3,336 X3 + 0,4070 X4 - 0,000822 X3*X3

Exhibit 4 Response Surface Regression Model Y2 vs X1, X2, X3, X4

Backward Elimination of Terms

Candidate terms: X1; X2; X3; X4; X1*X1; X2*X2; X3*X3; X4*X4; X1*X2; X1*X3; X1*X4; X2*X3; X2*X4; X3*X4

	---Step 1---		---Step 2---		---Step 3---		---Step 4---	
	Coef	P	Coef	P	Coef	P	Coef	P
Constant	32,73		32,73		32,73		32,311	
X1	4,550	0,000	4,550	0,000	4,550	0,000	4,550	0,000
X2	6,017	0,000	6,017	0,000	6,017	0,000	6,017	0,000
X3	-0,350	0,613	-0,350	0,598	-0,350	0,584	-0,350	0,574
X4	2,617	0,002	2,617	0,001	2,617	0,001	2,617	0,001
X1*X1	2,37	0,037	2,375	0,030	2,375	0,024	2,533	0,010
X2*X2	3,92	0,002	3,925	0,001	3,925	0,001	4,083	0,000
X3*X3	0,88	0,404	0,875	0,384	0,875	0,366	1,033	0,249
X4*X4	-0,48	0,647	-0,475	0,633	-0,475	0,620		
X1*X2	-4,00	0,005	-4,00	0,003	-4,00	0,002	-4,00	0,002
X1*X3	-0,10	0,933	-0,10	0,930				
X1*X4	1,85	0,139	1,85	0,123	1,85	0,109	1,85	0,100
X2*X3	0,95	0,432	0,95	0,413	0,95	0,395	0,95	0,382
X2*X4	-0,00	1,000						
X3*X4	2,70	0,039	2,70	0,032	2,70	0,026	2,70	0,022

S	2,33619	2,24454	2,16355	2,10929
R-sq	93,82%	93,82%	93,81%	93,70%
R-sq(adj)	86,60%	87,63%	88,51%	89,08%
R-sq(pred)	64,54%	68,00%	71,48%	73,88%
Mallows' Cp	15,00	13,00	11,01	9,23

	-----Step 5----		-----Step 6----		-----Step 7----	
	Coef	P	Coef	P	Coef	P
Constant	32,311		33,000		33,000	
X1	4,550	0,000	4,550	0,000	4,550	0,000
X2	6,017	0,000	6,017	0,000	6,017	0,000
X3	-0,350	0,571	-0,350	0,576	-0,350	0,595
X4	2,617	0,001	2,617	0,001	2,617	0,001
X1*X1	2,533	0,009	2,275	0,015	2,275	0,019
X2*X2	4,083	0,000	3,825	0,000	3,825	0,000
X3*X3	1,033	0,245				
X4*X4						
X1*X2	-4,00	0,002	-4,00	0,002	-4,00	0,002
X1*X3						
X1*X4	1,85	0,097	1,85	0,100		
X2*X3						
X2*X4						
X3*X4	2,70	0,020	2,70	0,021	2,70	0,027

S	2,09682	2,12483	2,24157
R-sq	93,36%	92,75%	91,46%
R-sq(adj)	89,20%	88,91%	87,66%
R-sq(pred)	75,33%	76,14%	74,58%
Mallows' Cp	7,89	7,06	7,57

α to remove = 0,05

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	8	968,46	121,058	24,09	0,000
Linear	4	766,47	191,617	38,14	0,000
X1	1	248,43	248,430	49,44	0,000
X2	1	434,40	434,403	86,45	0,000
X3	1	1,47	1,470	0,29	0,595
X4	1	82,16	82,163	16,35	0,001
Square	2	108,84	54,418	10,83	0,001
X1*X1	1	33,12	33,124	6,59	0,019
X2*X2	1	93,64	93,636	18,64	0,000
2-Way Interaction	2	93,16	46,580	9,27	0,002
X1*X2	1	64,00	64,000	12,74	0,002
X3*X4	1	29,16	29,160	5,80	0,027
Error	18	90,44	5,025		
Lack-of-Fit	16	89,94	5,621	22,19	0,044
Pure Error	2	0,51	0,253		
Total	26	1058,91			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2,24157	91,46%	87,66%	74,58%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	33,000	0,747	44,17	0,000	
X1	4,550	0,647	7,03	0,000	1,00
X2	6,017	0,647	9,30	0,000	1,00
X3	-0,350	0,647	-0,54	0,595	1,00
X4	2,617	0,647	4,04	0,001	1,00
X1*X1	2,275	0,886	2,57	0,019	1,04
X2*X2	3,825	0,886	4,32	0,000	1,04
X1*X2	-4,00	1,12	-3,57	0,002	1,00
X3*X4	2,70	1,12	2,41	0,027	1,00

Regression Equation in Uncoded Units

Y2 = 41,5 + 0,150 X1 - 0,0168 X2 - 0,02254 X3 - 0,00943 X4
+ 0,001422 X1*X1 + 0,000044 X2*X2 - 0,000338 X1*X2 + 0,000011 X3*X4

Exhibit 5 Response Surface Regression Model Y1 versus X1, X2, X3, X4 on Step 7

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	8	4847181	605898	51,32	0,000
Linear	4	4637667	1159417	98,21	0,000
X1	1	76800	76800	6,51	0,020
X2	1	448533	448533	37,99	0,000
X3	1	3392033	3392033	287,33	0,000
X4	1	720300	720300	61,02	0,000
Square	2	141014	70507	5,97	0,010
X2*X2	1	34614	34614	2,93	0,104
X3*X3	1	127314	127314	10,78	0,004
2-Way Interaction	2	68500	34250	2,90	0,081
X1*X3	1	32400	32400	2,74	0,115
X3*X4	1	36100	36100	3,06	0,097
Error	18	212493	11805		
Lack-of-Fit	16	211693	13231	33,08	0,030
Pure Error	2	800	400		
Total	26	5059674			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
108,652	95,80%	93,93%	89,63%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	2880,6	36,2	79,54	0,000	
X1	80,0	31,4	2,55	0,020	1,00
X2	193,3	31,4	6,16	0,000	1,00
X3	531,7	31,4	16,95	0,000	1,00
X4	245,0	31,4	7,81	0,000	1,00
X2*X2	-73,5	42,9	-1,71	0,104	1,04
X3*X3	-141,0	42,9	-3,28	0,004	1,04
X1*X3	-90,0	54,3	-1,66	0,115	1,00
X3*X4	-95,0	54,3	-1,75	0,097	1,00

Regression Equation in Uncoded Units

Y1 = -3255 + 8,91 X1 + 1,822 X2 + 4,730 X3 + 0,892 X4 - 0,000839 X2*X2
- 0,000918 X3*X3 - 0,00574 X1*X3 - 0,000403 X3*X4

Fits and Diagnostics for Unusual Observations

Obs	Y1	Fit	Resid	Std Resid	
26	3200,0	3004,3	195,7	2,18	R

R Large residual

Exhibit 6 Response Surface Regression Model Y2 versus X1, X2, X3, X4 on Step 6

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	982,15	109,128	24,17	0,000
Linear	4	766,47	191,617	42,44	0,000
X1	1	248,43	248,430	55,02	0,000
X2	1	434,40	434,403	96,22	0,000
X3	1	1,47	1,470	0,33	0,576
X4	1	82,16	82,163	18,20	0,001
Square	2	108,84	54,418	12,05	0,001
X1*X1	1	33,12	33,124	7,34	0,015
X2*X2	1	93,64	93,636	20,74	0,000
2-Way Interaction	3	106,85	35,617	7,89	0,002
X1*X2	1	64,00	64,000	14,18	0,002
X1*X4	1	13,69	13,690	3,03	0,100
X3*X4	1	29,16	29,160	6,46	0,021
Error	17	76,75	4,515		
Lack-of-Fit	15	76,25	5,083	20,06	0,048
Pure Error	2	0,51	0,253		
Total	26	1058,91			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2,12483	92,75%	88,91%	76,14%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	33,000	0,708	46,59	0,000	
X1	4,550	0,613	7,42	0,000	1,00
X2	6,017	0,613	9,81	0,000	1,00
X3	-0,350	0,613	-0,57	0,576	1,00
X4	2,617	0,613	4,27	0,001	1,00
X1*X1	2,275	0,840	2,71	0,015	1,04
X2*X2	3,825	0,840	4,55	0,000	1,04
X1*X2	-4,00	1,06	-3,77	0,002	1,00
X1*X4	1,85	1,06	1,74	0,100	1,00
X3*X4	2,70	1,06	2,54	0,021	1,00

Regression Equation in Uncoded Units

Y2 = 51,6 + 0,004 X1 - 0,0168 X2 - 0,02254 X3 - 0,01481 X4
+ 0,001422 X1*X1 + 0,000044 X2*X2- 0,000338 X1*X2 + 0,000077 X1*X4
+ 0,000011 X3*X4

Fits and Diagnostics for Unusual Observations

Obs	Y2	Fit	Resid	Std Resid	
9	46,20	42,49	3,71	2,04	R

R Large residual

Exhibit 7 Residual Plot of Y1 on Step 7

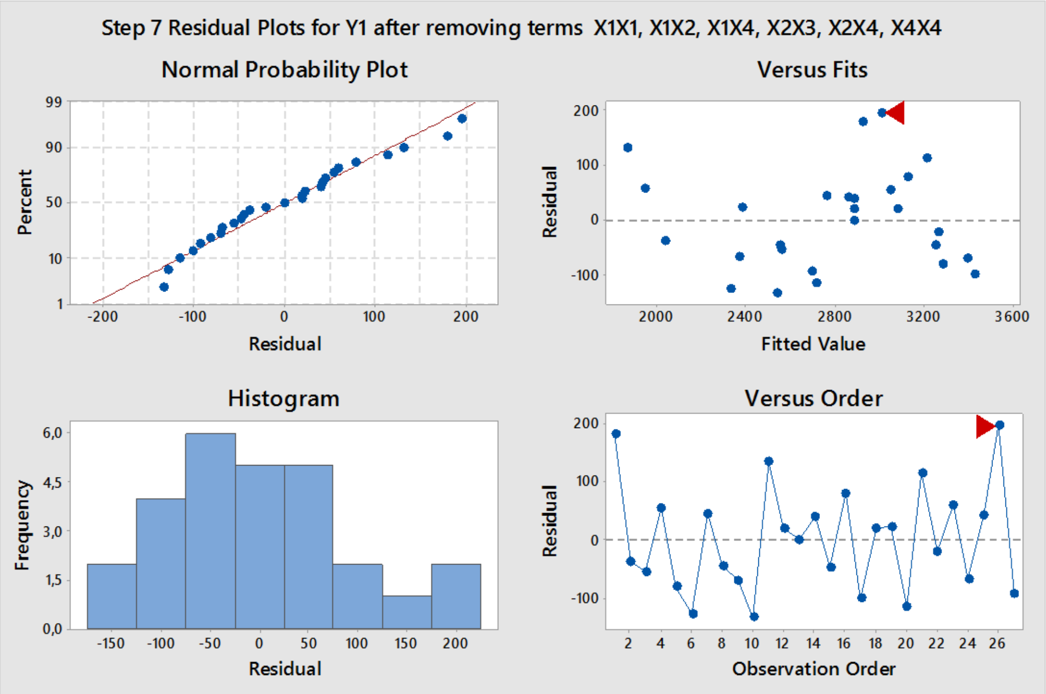


Exhibit 8 Residual Plot of Y2 on Step 6

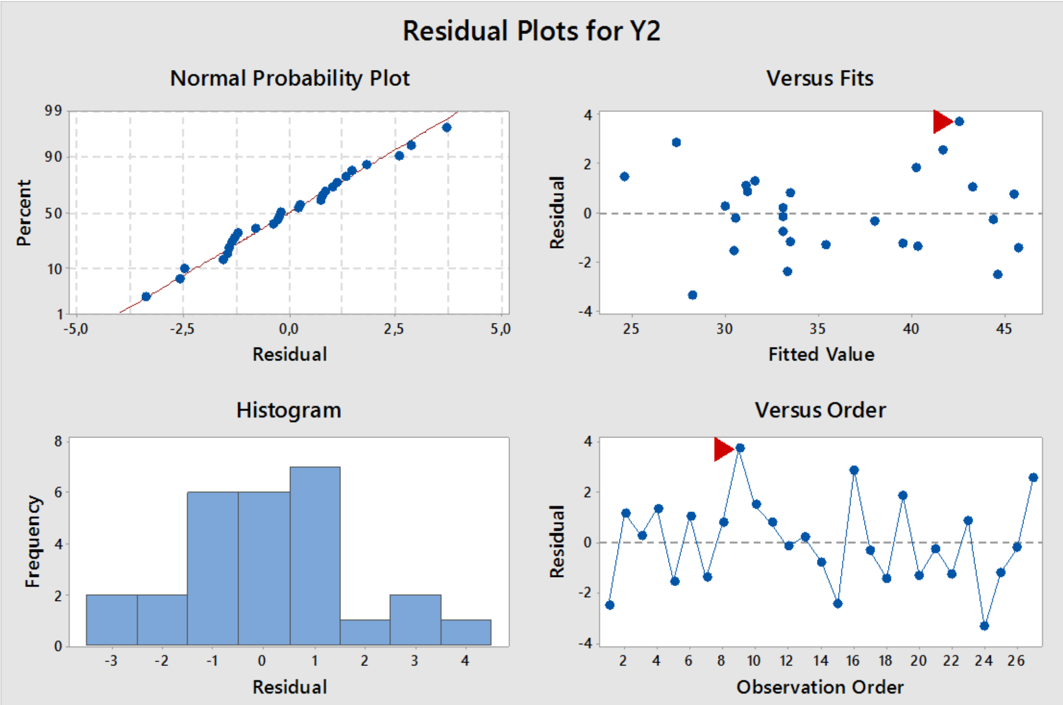


Exhibit 9 Cost Calculation

OPTIMIZED SOLUTIONS								
Data #	X1 [1]	X2 [2]	X3a [3]	X4 [4]	ΣXi [5]	Y1 [6]	Y2 [7]	Cost [$/Ton] [8]
1	93,9	400,0	1.239,6	2.494,0	4.227,6	3.039	40,0	62,91
2	71,1	717,1	1.270,6	2.034,9	4.093,7			64,20

Note :
Data 1 is from response optimizer jointly optimization of Y1 and Y2.
Data 2 id from response optimizer of Y3 = Y1 + Y2 with minimum value of Y3 = 3080, so that Y1 and Y2 individually not identified.

OPTIMIZED SOLUTIONS							
Data #	X1 [1]	X2 [2]	X3a [3]	X4 [4]	ΣXi [5]	Y1 [6]	Y2 [7]
1	104,3	577,6	1.241,3	2.171,0	4.094,2	3.011	39,0
2	101,7	525,0	1.221,4	2.270,4	4.118,5	2.979	39,1
3	98,7	461,1	1.251,3	2.339,2	4.150,3	2.966	39,2
4	97,2	461,1	1.221,4	2.415,6	4.195,3	2.965	39,1
5	101,2	442,3	1.246,3	2.369,8	4.159,6	2.957	40,4
6	**110,0**	**992,0**	**1.593,6**	**1.340,4**	**4.035,9**	**3.242**	**38,1**
7	110,0	992,0	1.500,5	1.323,7	3.926,2	3.170	38,6
8	110,0	992,0	1.430,6	1.307,0	3.839,7	3.104	39,0
9	110,0	992,0	1.410,5	1.368,9	3.881,4	3.105	39,8
10	93,9	400,0	1.239,6	2.494,0	4.227,6	3.039	40,0

UNIT PRICE OF MATERIALS			
No.	Material Description	Density [Ton/m3]	Unit Price [USD/Ton]
1	X1 = Water	1,00	0,6
2	X2 = Portland cement	3,15	104
3	X3a = Crushed stone	2,64	20
4	X3b = Fine iron ore	3,00	50
5	X4 = Coarse iron ore	4,00	80

UNIT PRICE OF MATERIALS			
No.	Material Description	Density [Ton/m3]	Unit Price [USD/Ton]

Example:
Design mix #1.
Cost of water (X1) = 93,9 (kg) x 0,6 (USD/Ton) /1000 = 0,06 USD
Cost of cement (X2) = 400 (kg) x 104 (USD/Ton)/1000 = 41,6 USD
Cost of Crushed stone = 1239,6 (kg) x 20 (USD/Ton)/1000 = 24,79 USD
Cost of iron ore coarse = 2494 (kg) x 80 (USD/Ton)/1000 = 199,5 USD
Total cost of material = 0,056 + 41,6 + 24,79 + 199,5 = 265,95 USD
The total weight = 93,9 + 400 + 1239,6 + 2494 = 4227,5 kg
Cost of concrete per ton = 258,64 (USD)/(4094,2/1000) (Ton) = 62,91 USD/Ton

Exhibit 10 Cost of Concrete Per Ton (Current State)

PRODUCTION RECORDS (CURRENT STATE)				
Description	X1	X2	X3b	X4
Proportion	0,05	0,24	0,24	0,47
Density [Ton/m3]	1,00	3,15	3,00	4,00
Weight [Ton]	0,053	0,749	0,717	1,882
Unit Price	0,6	104	50	80
Cost [USD]	0,03	77,85	35,86	150,55
Total Cost [USD]	264,3			
Total Weight [Ton]	3,4			
Unit Cost [USD/Ton]	77,7			

Notes :
X1 = Water
X2 = Cement
X3b = Fine aggregate iron ore
X4 = Coarse aggregate iron ore

PRODUCTION RECORDS (CURRENT STATE)			
Description	X1	X2	X3b
Proportion	0,05	0,24	0,24
Density [Ton/m3]	1,00	3,15	3,00
Weight [Ton]	0,053	0,749	0,717
Unit Price [USD/Ton]	0,6	104	50
Cost [USD]	0,03	77,85	35,86
Total Cost [USD]	264,3		
Total Weight [Ton]	3,4		
Unit Cost [USD/Ton]	77,7		

Notes :
X1 = Water
X2 = Cement

X3b = Fine aggregate iron ore
X4 = Coarse aggregate iron ore

Source : PT XYZ

Exhibit 11 REGRESSION AND OPTIMIZATION OF Y3 = Y1+Y2

Response Surface Regression: Y3=Y1+Y2 versus X1; X2; X3; X4

Backward Elimination of Terms

Candidate terms: X1; X2; X3; X4; X1*X1; X2*X2; X3*X3; X4*X4; X1*X2; X1*X3; X1*X4; X2*X3; X2*X4; X3*X4

	--Step 1--		--Step 2--		--Step 3--		--Step 4--	
	Coef	P	Coef	P	Coef	P	Coef	P
Constant	2932,6		2936,4		2925,3		2925,3	
X1	84,5	0,017	84,5	0,012	84,5	0,010	84,5	0,008
X2	214,9	0,000	214,9	0,000	214,9	0,000	214,9	0,000
X3	515,2	0,000	515,2	0,000	515,2	0,000	515,2	0,000
X4	247,6	0,000	247,6	0,000	247,6	0,000	247,6	0,000
X1*X1	-15,3	0,743	-16,7	0,692				
X2*X2	-93,0	0,064	-94,4	0,040	-90,2	0,035	-90,2	0,031
X3*X3	-163,5	0,004	-165,0	0,002	-160,8	0,001	-160,8	0,001
X4*X4	4,4	0,926						
X1*X2	-54,0	0,325	-54,0	0,305	-54,0	0,289	-54,0	0,277
X1*X3	-90,1	0,112	-90,1	0,098	-90,1	0,087	-90,1	0,080
X1*X4	31,8	0,556	31,8	0,540	31,8	0,526	31,8	0,516
X2*X3	27,5	0,611	27,5	0,596	27,5	0,584		
X2*X4	-50,0	0,361	-50,0	0,341	-50,0	0,325	-50,0	0,313
X3*X4	-92,3	0,105	-92,3	0,091	-92,3	0,081	-92,3	0,073
S	105,217		101,128		98,0642		95,7975	
R-sq	97,33%		97,33%		97,30%		97,23%	
R-sq(adj)	94,22%		94,66%		94,98%		95,21%	
R-sq(pred)	84,63%		86,14%		87,68%		89,34%	
Mallows' Cp	15,00		13,01		11,16		9,43	

	--Step 5----		--Step 6----		--Step 7----		--Step 8----	
	Coef	P	Coef	P	Coef	P	Coef	P
Constant	2925,3		2925,3		2925,3		2925,3	
X1	84,5	0,007	84,5	0,006	84,5	0,007	84,5	0,009
X2	214,9	0,000	214,9	0,000	214,9	0,000	214,9	0,000
X3	515,2	0,000	515,2	0,000	515,2	0,000	515,2	0,000
X4	247,6	0,000	247,6	0,000	247,6	0,000	247,6	0,000
X1*X1								
X2*X2	-90,2	0,027	-90,2	0,027	-90,2	0,028	-90,2	0,037
X3*X3	-160,8	0,001	-160,8	0,000	-160,8	0,000	-160,8	0,001
X4*X4								
X1*X2	-54,0	0,268	-54,0	0,269				
X1*X3	-90,1	0,074	-90,1	0,073	-90,1	0,075		
X1*X4								
X2*X3								
X2*X4	-50,0	0,304						
X3*X4	-92,3	0,067	-92,3	0,067	-92,3	0,069	-92,3	0,085
S	94,1126		94,4691		95,2713		101,528	
R-sq	97,15%		96,95%		96,72%		96,07%	
R-sq(adj)	95,37%		95,34%		95,26%		94,62%	
R-sq(pred)	90,71%		90,36%		91,64%		90,69%	
Mallows' Cp	7,80		6,70		5,76		6,69	

```
             -----Step 9----
               Coef        P
Constant     2925,3
X1             84,5    0,013
X2            214,9    0,000
X3            515,2    0,000
X4            247,6    0,000
X1*X1
X2*X2         -90,2    0,046
X3*X3        -160,8    0,001
X4*X4
X1*X2
X1*X3
X1*X4
X2*X3
X2*X4
X3*X4

S                    107,221
R-sq                  95,38%
R-sq(adj)             94,00%
R-sq(pred)            91,18%
Mallows' Cp             7,77

α to remove = 0,05

Model Summary
```

STEPS	1	2	3	4	5	6	7	8	9
S	105,22	101,13	98,06	95,80	94,11	94,47	95,27	101,53	107,22
R-sq [%]	97,33	97,33	97,30	97,23	97,15	96,95	96,72	96,07	95,38
R-sq(adj) [%]	94,22	94,66	94,98	95,21	95,37	95,34	95,26	94,62	94,00
R-sq(pred) [%]	84,63	86,14	87,68	89,34	90,71	90,36	91,64	90,69	91,18
Mallows' Cp	15,00	13,01	11,16	9,43	7,80	6,70	5,76	6,69	7,77

Upto step 7, the model getting better but from step 8 to step 9 the model is becoming worse and worse. It is decided to stop upto step 7.

Response Surface Regression: Y3=Y1+Y2 versus X1; X2; X3; X4

Terms eliminated: X1*X1, X4*X4, X1*X2, X1*X4, X2*X3, X2*X4

```
Analysis of Variance

Source                DF   Adj SS   Adj MS  F-Value  P-Value
Model                  8  4814820   601852    66,31    0,000
  Linear               4  4560325  1140081   125,61    0,000
    X1                 1    85784    85784     9,45    0,007
    X2                 1   554012   554012    61,04    0,000
    X3                 1  3184760  3184760   350,88    0,000
    X4                 1   735768   735768    81,06    0,000
  Square               2   187945    93973    10,35    0,001
    X2*X2              1    52114    52114     5,74    0,028
    X3*X3              1   165457   165457    18,23    0,000
  2-Way Interaction    2    66549    33275     3,67    0,046
    X1*X3              1    32472    32472     3,58    0,075
    X3*X4              1    34077    34077     3,75    0,069
Error                 18   163379     9077
  Lack-of-Fit         16   163374    10211  4433,10    0,000
```

```
  Pure Error          2        5        2
Total                26  4978199
```

Model Summary

```
      S    R-sq  R-sq(adj)  R-sq(pred)
95,2713  96,72%     95,26%      91,64%
```

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	2925,3	31,8	92,11	0,000	
X1	84,5	27,5	3,07	0,007	1,00
X2	214,9	27,5	7,81	0,000	1,00
X3	515,2	27,5	18,73	0,000	1,00
X4	247,6	27,5	9,00	0,000	1,00
X2*X2	-90,2	37,7	-2,40	0,028	1,04
X3*X3	-160,8	37,7	-4,27	0,000	1,04
X1*X3	-90,1	47,6	-1,89	0,075	1,00
X3*X4	-92,3	47,6	-1,94	0,069	1,00

Regression Equation in Uncoded Units

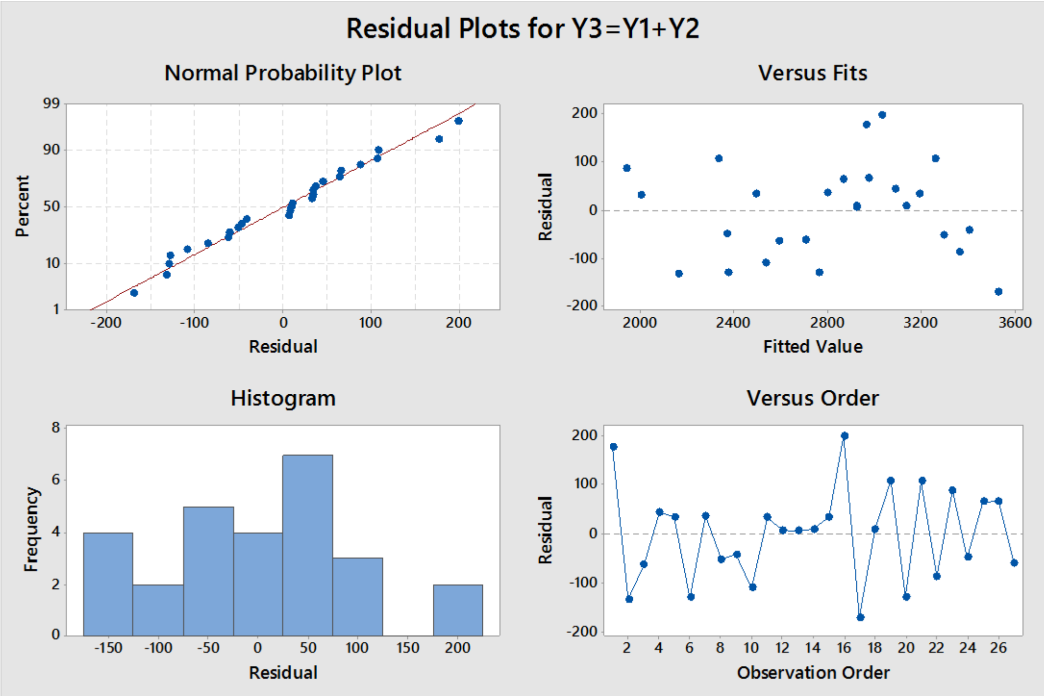
```
Y3=Y1+Y2 =  -3479 + 9,03 X1 + 2,160 X2 + 4,976 X3 + 0,882 X4
            - 0,001030 X2*X2 - 0,001046 X3*X3 - 0,00575 X1*X3
            - 0,000391 X3*X4
```

Fits and Diagnostics for Unusual Observations

Obs	Y3=Y1+Y2	Fit	Resid	Std Resid	
1	3142,0	2965,3	176,7	2,17	R

R Large residual

Residual Plots for Y3=Y1+Y2



Response Optimization: Y3=Y1+Y2

Parameters

Response	Goal	Lower	Target	Upper	Weight	Importance
Y3 =Y1+Y2	Target	3040	3080	3440	1	1

Solution

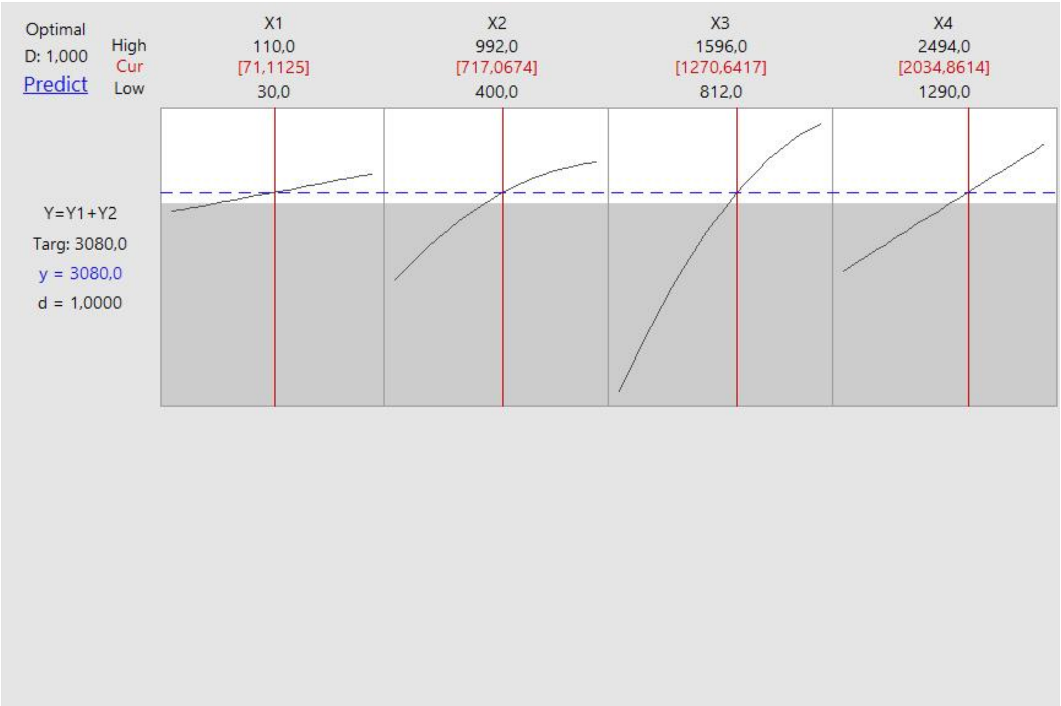
Solution	X1	X2	X3	X4	Y3=Y1+Y2 Fit	Composite Desirability
1	71,1125	717,067	1270,64	2034,86	3080	1

Multiple Response Prediction

Variable	Setting
X1	71,1125
X2	717,067
X3	1270,64
X4	2034,86

Response	Fit	SE Fit	95% CI	95% PI
Y3=Y1+Y2	3080,0	32,1	(3012,5; 3147,5)	(2868,8; 3291,2)

Optimization Plot



The optimum mix of Y3 = Y1 + Y2 is as follow

X1 = 71,1

X2 = 717,1

X3 = 1270,6

X4 = 2034,9

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BIOGRAPHY

SIENS HARIANTO, born in Blitar at April 23, 1961. Graduated from Bandung Institute of Technology in 1986 majoring in Mechanical Engineering. Since then he worked in the manufacturing of steel pipe and anti-corrosion coating company in the Banten Province for 11 years before he run his own consulting company in 1997.

He has been working as technical consultant of PT Indal Steel Pipe in East Java since 1997 for quality management, production management, engineering construction, and project management in the oil and gas business. In 2014 he participated in Master Program at MMT-ITS for Industrial Management, with a final thesis

"DESIGN MIX OPTIMIZATION OF HEAVY WEIGHT CONCRETE COATING PROCESS AT PT XYZ BY BOX-BEHNKEN DESIGN EXPERIMENT".